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The Number and Quality of Representations in Working Memory

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Abstract

Some theories characterize working memory as a flexible resource that can store a large number of low-quality representations or a small number of high-quality representations. Other theories propose that the number of items that can be stored in working memory is strictly limited and cannot be increased by decreasing the quality of the representations. We tested these fundamentally different conceptualizations of working memory capacity by asking whether observers could trade quality for quantity when given incentives to do so. We found no evidence that observers could increase the number of representations by decreasing the quality of the representations in working memory, but they could do so at earlier processing stages. Thus, the capacity limit in working memory is best characterized as a limit on the number of items that can be stored, not as a limit in a finely divisible resource that simultaneously determines the number and quality of the representations.

The limited capacity of working memory plays a key role in both classic and contemporary theories of cognition (Cowan, 2005; Miller, 1956). Moreover, individual differences in working memory capacity predict differences in a wide range of higher cognitive abilities. This predictive ability appears to be particularly strong for visual working memory (VWM) capacity, which accounts for over 40% of the variance in global fluid intelligence (Fukuda, Vogel, Mayr, & Awh, 2010) and almost 80% of the variance in overall cognitive performance (Gold et al., 2010). VWM capacity also varies across the lifespan (Gazzaley, Cooney, Rissman, & D'Esposito, 2005) and is reduced in psychiatric disorders (Gold, et al., 2010). Understanding VWM capacity limits is therefore essential for understanding the human mind.

Two broad classes of theories of VWM capacity have been proposed (reviewed by Luck, 2008). *Flexible resource theories* propose that VWM capacity reflects the flexible allocation of a limited pool of a cognitive resource. According to these theories, allocating more resources to an item will allow that item to be represented with greater quality or precision (Bays & Husain, 2008; Palmer, 1990; Wilken & Ma, 2004). That is, resources can be focused on a small number of items to create high-quality representations or distributed among a large number of items to create low-quality representations. In contrast, *limited-item theories* propose that K is strictly limited for a given individual and cannot be increased by decreasing the precision of the representations (Anderson, Vogel, & Awh, 2011; Zhang & Luck, 2008). In these theories, VWM capacity is analogous to a set of slots rather than a pool of resources.

These theories are more easily tested with simple, unidimensional features, for which the concept of precision can be unambiguously operationalized. Several recent studies have used this approach, testing memory for arrays of single-feature items and measuring how precision and K vary as the number of to-be-remembered items (the *set size*) varies. Some of

these studies found that K increases and precision decreases as the set size increases up to 3–4 items, at which point both K and precision reach an asymptote (Anderson, et al., 2011; Zhang & Luck, 2008). These studies support limited-item theories of VWM capacity. However, other studies have found no asymptote for either K or precision (Bays & Husain, 2008; Wilken & Ma, 2004), supporting flexible-resource theories.

These studies varied the number of items in the display, assuming that observers would attempt to store as many items as possible in VWM. However, it is possible that observers would strategically decide to devote all of their resources to a limited number of items at large set sizes even if they could, in principle, store low-quality representations of every item. The present study therefore took a different approach, assessing the most fundamental difference between flexible-resource and limited-item theories, which is whether people can increase the number of items stored by decreasing the quality of the representations if motivated to do so.

Experiments 1–3 used three different methods to motivate observers to store a large number of low-precision representations. All three of these approaches failed to produce an increase in the number of items stored in VWM. Experiment 4 demonstrated that these failures were not caused by weak manipulations of motivation, because tradeoffs could be produced between K and precision in iconic memory. Thus, our manipulations were strong enough to influence iconic memory, but they could not induce a tradeoff between quality and quantity in working memory.

Experiments 1a and 1b

To independently measure K and precision, we used a VWM recall task in which observers stored a set of colors in memory and then reported the color of one item—indicated by a probe at the time of test—by clicking on a color wheel (Figure 1a; see Zhang & Luck, 2008). If the probed item is present in VWM, then the observer's response should be near the correct color, and errors should be distributed normally around the correct color. If, however, the probed item is absent from memory, then the observer will guess randomly, leading to a uniform distribution of errors. If the observer remembers the probed item on some trials and guesses randomly on other trials, the overall distribution of errors will consist of a mixture of a normal distribution and a uniform distribution, which is simply a normal distribution with a vertical offset. It is possible to mathematically decompose this mixture into its components. The standard deviation (SD) of the normally distributed portion of the mixture reflects the precision of the memory representation when the probed item was present in memory. The amount of vertical offset can be used to determine the probability that the probed item was present in memory, and the number of items in memory (K) is the set size multiplied by this probability. This analytic approach has been used in several recent studies (Anderson, et al., 2011; Zhang & Luck, 2008, 2009).

In Experiments 1a and 1b, we manipulated the amount of precision needed to perform this task by varying the number of distinct colors in the color wheel. In the high-precision condition (Figure 1a), the color wheel contained 180 equally spaced color values, and participants were given feedback about the distance between the actual color and the reported color (i.e., the magnitude of the recall error). A very precise representation is needed to minimize the error in this condition. In the low-precision condition (Figure 1b), the color wheel contained a small set of discrete “spokes.” A relatively imprecise representation would be sufficient to produce a correct response in this condition, and overall performance would therefore be maximized by storing a large number of low quality representations in VWM. If observers can increase K by decreasing precision, then they should store more items in the low-precision condition than in the high-precision condition.

Method

Participants—The observers were UC Davis students between the ages of 18 and 30 with normal color vision and normal or corrected-to-normal visual acuity (separate groups of 13 for each experiment).

Stimuli and Procedure—Stimuli were presented on a CRT with a gray background (15.1 cd/m^2) and a continuous fixation point at a viewing distance of 57 cm. Each trial began with a 200-ms sample array consisting of four colored squares ($2 \times 2^\circ$). The colors were selected from a master set of 180 evenly distributed and isoluminant hues on a circle in the perceptually homogeneous CIELAB color space (for details, see Zhang & Luck, 2008).

After a 1000-ms delay, a test array was presented, consisting of outlined squares at each sample location and a color wheel (8.2° diameter; 2.2° thickness). The *probe square* was thicker than the other squares and indicated that the observer should report the color of the corresponding sample square. The color wheel consisted of all 180 colors in the high-precision condition. In the low-precision condition, it consisted of 9 (Experiment 1a) or 6 (Experiment 1b) color “spokes” (0.29° wide); one of the spokes was the same color as the probed sample, and the colors of the other spokes were selected to be at 40° (Experiment 1a) or 60° (Experiment 1b) increments from this color. In both conditions, observers were instructed to make a mouse click on the color that exactly matched the color of the probed sample square, taking as much time as needed. Each of the colors in the sample array was one of the colors present in the array of spokes; consequently, these colors were separated by multiples of 40° (Experiment 1) or 60° (Experiment 2), in both the low- and high-precision conditions. Feedback was provided by markers indicating the correct answer (arrow) and the reported color (cross), with the angular differences between the two markers representing the error magnitude. Each observer received 24 practice trials and 150 experimental trials in each condition, and the order of conditions was counterbalanced across observers.

Maximum likelihood estimation was used to determine the SD and K parameters (for details, see Zhang & Luck, 2008). Note, however, that none of the conclusions of this study depend on the use of this specific quantitative model (see online supplementary materials).

Results and Discussion

Figure 1 shows the K and SD estimates (see online supplementary materials for raw data and goodness of fit). For both experiments, the number of items in memory (K) was nearly identical in the low-precision and high-precision conditions¹. The low- and high-precision conditions were not significantly different in paired t-tests [$t(12) = .80$, $p = .43$ for Experiment 1a; $t(12) = 1.20$, $p = .25$ for Experiment 1b]. A Bayes Factor analysis (Rouder, Speckman, Sun, Morey, & Iverson, 2009) indicated that the null hypothesis (no difference between the low- and high-precision conditions) was 3.57 times more likely to be true than the alternative hypothesis (a difference between conditions) for Experiment 1a; this ratio was 2.52 for Experiment 1B. In addition, confidence interval analyses indicated that we can be 95% confident that K was increased in the low-precision condition relative to the high-precision condition by no more than 0.24 items in Experiment 1a and no more than 0.08 items in Experiment 1b. Thus, although it is impossible to prove the null hypothesis, these results show that null hypothesis was substantially more likely to be true than the alternative

¹The K values were considerably lower in Experiment 1a than in Experiment 1b, but this likely reflects random differences between the participants in the two experiments. More generally, the K values observed with the color wheel recall paradigm used in this study tend to be lower than those observed with change detection paradigms. However, the K values are highly correlated across paradigms (Zhang & Luck, 2008; Gold et al., 2010).

hypothesis and that, even if there was a real effect, it was very small (less than a quarter of an item's worth of increased capacity in the low-precision condition).

There was also no hint of reduced precision (increased SD) in the low-precision condition relative to the high-precision condition of Experiment 1a (SD could not be meaningfully estimated in with only 6 response alternatives Experiment 1b). The difference in SD between conditions was not significant [$t(12) = .65$, $p = .53$], and the Bayes Factor analysis indicated that the null hypothesis was 3.96 times more likely than the alternative hypothesis. In addition, a confidence interval analysis indicated that we can be 95% confident that the SD was no more than 4.82° greater in the high-precision condition than in the low-precision condition.

These results indicate that observers cannot increase the number of items in VWM or decrease the precision of the representations when the task is changed to require less precision.

Experiment 2

Experiment 2 used a different method to encourage observers to reduce precision and therefore increase the number of items stored in VWM. Rather than providing exact feedback about the difference between the reported color and the correct color, observers were simply told whether the response was correct or incorrect. In the low-precision condition, a response was considered correct if it was within $\pm 60^\circ$ of the original color value; in the high-precision condition, a response was considered correct if it was within $\pm 15^\circ$ of the original value. Thus, if it is possible to trade off precision for capacity, observers could maximize performance in the low-precision condition by maintaining a large number of imprecise representations. This approach also eliminated the physical differences between the color spokes and color wheel in Experiment 1.

This manipulation can also be conceived as requiring different decision criteria in the different conditions, an approach that has been used for decades to distinguish between continuous and discrete processes in signal detection theory (Atkinson & Juola, 1973, 1974; Mandler, 1980).

Method

The methods were the same as in the high-precision condition of Experiment 1a, except as follows. A new sample of 14 observers was tested. Feedback about response accuracy was provided after the observer's response by providing a white arc that was either 30° (high-precision condition) or 120° (low-precision condition). This arc was superimposed on the color wheel, centered at the location of the correct color. In principle, observers could have used the midpoint of the arc to determine the actual distance between the response and the original color, but they were instructed that the goal was solely to make sure that the response was somewhere within the range indicated by the arc and were not informed that the midpoint of the arc denoted the correct color.

Results and Discussion

The K and SD values are shown in Figure 2. Observers stored an average of 2.44 items in both the low- and high-precision conditions. These values were not significantly different [$t(13) = .39$, $p = .71$], and the Bayes Factor analysis indicated that the null hypothesis was 4.64 times more likely to be true than the alternative hypothesis. In addition, a confidence interval analysis indicated that we can be 95% confident that K was no more than 0.40 items greater in the low-precision condition than in the high-precision condition. This experiment

provides converging evidence against the hypothesis that the number of items stored in VWM can be increased by reducing the precision of the representations.

The responses were slightly more precise in the high-precision condition than in the low-precision condition, and this small difference was marginally significant [$t(13) = 2.12$, $p = .054$]. However, the Bayes factor analysis indicated that a real difference between conditions was only 1.27 times more likely to be true than the null hypothesis. Moreover, even if this difference was real, it was only a 2° difference, which is tiny relative to the 90° difference in the precision requirements of the low- and high-precision conditions.

Experiment 3

It is possible that observers in Experiments 1 and 2 were not sufficiently motivated to decrease precision, and Experiment 3 therefore provided monetary incentives. Specifically, observers earned money for responses that were within $\pm 10^\circ$ (high-precision condition) or $\pm 60^\circ$ (low-precision condition) of the actual color. Observers could earn 38% more money in the low-resolution condition by reducing precision and increasing the number of items stored in VWM.

Method

The methods were the same as in the high-precision condition of Experiment 1a, except as follows. A new sample of 10 observers was tested. The amount of money earned on each trial and the total earnings were indicated by two numbers at the center of the screen. In the high-precision condition, observers earned \$.06 if the response fell within $\pm 10^\circ$ of the original color value and received nothing otherwise. In the low-precision condition, observers earned \$.04 if the response fell within $\pm 60^\circ$ of the original color value, and they earned nothing if the response fell 60-100° from the original value. To encourage observers to store at least some information about every item in memory in the low-precision condition, they were penalized \$.02 for wild guesses (responses that were more than 100° from the original color value). In addition, observers also received a base payment of 10 dollars. The observers were fully informed of the payment contingencies.

Results and Discussion

The K and SD values are shown in Figure 2b. The K values in the low- and high-precision conditions were nearly identical and were not significantly different [$t(9) = 1.39$, $p = .20$]. The Bayes Factor analysis indicated that the null hypothesis was 1.87 times more likely to be true than the alternative hypothesis. In addition, a confidence interval analysis indicated that we can be 95% confident that K was no more than 0.32 items greater in the low-precision condition than in the high-precision condition. The payoff manipulation also had no significant impact on SD [$t(9) = .64$, $p = .54$]. The null hypothesis for SD was 3.56 times more likely than the alternative hypothesis, and we can be 95% confident that the SD was no more than 4.90° greater in the low-precision condition than in the high-precision condition.

Observers earned an average of \$13.69 in both the low- and high-precision conditions. To maximize earnings, the optimal SD would have been 25.2° in the high-precision condition and 38.8° in the low-precision condition (assuming the K-SD tradeoff proposed by Bays & Husain, 2008; see online supplementary materials). The observed SD of 24.7° in the high-precision condition was close to optimal. However, the observed SD of 26.2° in low-resolution condition was significantly less than the optimal value of 38.8° [$t(9) = 3.35$, $p = .004$], and observers would have increased their incentive-based earnings by 38% if they had been able to achieve the optimal SD in this condition. Thus, even in the presence of financial incentives, observers are unable to strategically increase the number of items stored in working memory by reducing the precision of the representations. Experiment 4 was

designed to demonstrate that our incentive structure was sufficiently powerful to influence tradeoffs under conditions with minimal VWM involvement.

Experiments 4a and 4b

Research in computational neuroscience has suggested that the underlying neural systems involved in VWM necessarily lead to a limited number discrete representations (Raffone & Wolters, 2001; Wang, 2001). However, there is no reason to believe that earlier stages of visual representation are subject to these same limits. In fact, tradeoffs between the number of attended items and their resolution have been demonstrated many times in studies of perception (Alvarez & Franconeri, 2007; Eriksen & Yeh, 1985; Horowitz & Cohen, 2010; Howard & Holcombe, 2008; Shulman, Wilson, & Sheehy, 1985; Treisman & Gormican, 1988). Thus, in Experiment 4 we sought to determine whether payoff manipulations could influence performance under conditions that were not limited by VWM storage. In Experiment 4a, we eliminated the delay between the offset of the sample array and the onset of the probe, allowing observers to use the probe to select information from higher-capacity, more fragile memory systems (Landman, Spekrijse, & Lamme, 2003; Sperling, 1960). We manipulated the payoffs as in Experiment 3, with the prediction that observers would be able to trade precision and number of items in this situation. Experiment 4b was identical to Experiment 4a except that a delay was included, as in Experiment 3, to force the use of VWM.

Method

The methods were the same as in Experiment 3, except as follows. To avoid ceiling effects, the set size was increased to 6 items. To avoid masking of iconic memory, the probe array was replaced with a single probe arrow adjacent to the probed location. To further minimize masking, the color wheel was presented simultaneously with the sample array, but with a random rotation. In addition, observers earned points without monetary value because pilot testing indicated that monetary incentives were unnecessary. The delay between the sample array and the probe was eliminated in Experiment 4a to minimize the use of VWM, but was reinstated in Experiment 4b. New samples of 9 and 12 observers were tested in Experiments 4a and 4b, respectively.

Results and Discussion

The K and SD values are shown in Figure 2c and 2d. The results from Experiment 4b, in which VWM was required, were very much like those from Experiment 3, with no changes in K or SD between the low- and high-precision conditions [$t(11)=0.06$, $p = 0.95$ for K; $t(11)=0.57$, $p = 0.58$ for SD]. The Bayes Factor analysis favored the null hypothesis by a factor of 4.65 for K and 4.00 for SD, and we can be 95% confident that any increase in the low-resolution condition was no more than 0.24 for K and nor more than 1.62 for SD. Thus, when performance was limited by VWM, we again found that observers cannot trade precision for an increase in the number of items in memory.

In Experiment 4a, which minimized VWM involvement, K increased significantly from 2.76 in the high-precision condition to 3.96 in the low-precision condition [$t(8)=3.76$, $p = 0.006$], and this was accompanied by a significant change in SD from 13.0° to 23.4° [$t(8)=3.31$, $p = 0.011$]. That is, providing incentives for low precision led to a nearly two-fold change in precision and a 43% increase in K. These effects were 10.7 and 6.1 times more likely to be true than the null hypothesis, respectively. Thus, even though the incentives were not monetary, observers could trade off precision and number of items when performance was based primarily on processes that precede VWM encoding.

Statistical comparisons of Experiments 4a and 4b were performed with a mixed-model two-way analyses of variance. The finding of differences in K and SD between the low- and high-precision conditions in Experiment 4a, but not in Experiment 4b, led to a significant interaction between experiment and condition for both K [$F(1,19)=9.18$, $p=0.007$] and SD [$F(1,19)=4.53$, $p=0.04$]. Thus, incentives had no impact on K or SD when the task stressed VWM, but they had a large effect when the task stressed perception and iconic memory.

General Discussion

The present results provide multiple pieces of converging evidence that VWM capacity is characterized by a limit on the number of items rather than by a finely divisible pool of resources. We repeatedly found that observers could not increase the number of VWM representations by reducing the precision of the representations, whether motivated to do so by the number of response alternatives, by the granularity of the feedback, or by direct incentives. In contrast, we found that observers could trade off precision and number of items at an earlier stage of representation, consistent with previous psychophysical and electrophysiological studies.

The present results should not be taken to imply that VWM precision is completely inflexible. Other research shows that precision and number of items can trade off in VWM when the number of items is below the item limit: precision can be increased when attention is focused on a single item by a spatial cue (Zhang & Luck, 2008) or by payoffs (Zhang & Luck, in preparation). These results fit with studies showing that precision increases as set size decreases below the item limit (Anderson, et al., 2011; Zhang & Luck, 2008). Thus, precision can be strategically increased by focusing resources onto a smaller number of items (see Zhang & Luck, 2008, for a quantitative model of resource allocation within VWM). However, there is a limit on the number of items that can be stored, and this limit cannot be exceeded by reducing the quality or complexity of the representations (Alvarez & Cavanagh, 2004; Awh, Barton, & Vogel, 2007; Barton, Ester, & Awh, 2009).

The item limit may arise from the need to keep individual VWM representations segregated from each other to avoid interference that would produce all-or-none collapse of the representations (e.g., Raffone & Wolters, 2001). Consequently, the overall storage capacity of VWM may be modifiable by factors that influence the segregation of representations. For example, extensive training may increase K by optimizing the segregation processes (Klingberg, 2010; Scolari, Vogel, & Awh, 2008). K may also be increased by means of chunking strategies that allow more efficient use of each representation (Miller, 1956).

Chunking strategies may explain previous studies in which observers appeared to trade off precision and capacity (e.g., Bays & Husain, 2008; Wilken & Ma, 2004). For example, an observer who is shown 20 haphazardly scattered dots might organize the dots into 4 clusters and store the centroid of each cluster in VWM. Only four representations would be present in VWM, but all 20 dots would contribute to these representations. If asked to report the remembered location of a single dot, the observer could use the stored cluster centroids to make an informed guess, and the precision of this response would be related to the number of dots in each cluster. In this manner, observers could use a small set of discrete representations to flexibly represent a large number of items at the cost of reduced precision. Precision and number of items would trade off from the perspective of performance, but there would still be a strict item limit from the perspective of the underlying representational structure and neurobiology.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

(a) Trial structure in the high-precision condition of Experiment 1a. (b) Example test display in the low-precision condition with 9 spokes. (c) Results from Experiment 1a, showing the number of items stored in memory (K) and the precision of the representations (inversely related to the standard deviation, SD). (d) Capacity results from Experiment 1b (SD could not be estimated reliably in this experiment given the granularity of the test display). Error bars in all data figures represent within-subjects 95% confidence intervals (Cousineau, 2007).

Figure 2. Capacity (K) and standard deviation (SD) results from Experiment 2 (a), Experiment 3 (b), Experiment 4a (c), and Experiment 4b (d).