# Individual Variation in Optimal Encoding Strategy in Visual Working Memory

Thesis

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Abstract

Extensive research has shown that differences in cognitive ability predict working memory (WM) performance. However, strategy use may also explain individual differences in WM performance. Here we explored the degree to which individuals use the optimal encoding strategy in visual WM. Participants searched for a target that changed between two alternating displays that cycled until response. Critically, participants were free to *choose* between two available targets (one red and one blue), and the ratio of red to blue items varied from trial to trial. Therefore, the optimal encoding strategy was to selectively encode items in the smaller colour subset. While choosing the optimal (small subset) target indeed led to better performance, there were large individual differences in strategy choice, with many participants using sub-optimal strategies. Interestingly, Experiment 1 found that WM ability does not predict strategy use. Experiment 2 showed that strategy use was not stable over time. Instead, many participants spontaneously shifted to highly-optimal target choices, suggesting a sudden discovery of the optimal strategy. Experiment 3 further suggests that explicit knowledge plays an important role in strategy choice. Providing information about the optimal strategy induced a large strategy change. Moreover, optimally-performing participants demonstrated explicit awareness of the optimal strategy. In Experiment 4, we found that even under greater task demands, when participants viewed the displays only once, strategy use was still sub-optimal. Our findings highlight strategy choice as an important source of individual variation, and therefore should be considered alongside ability to fully understand differences in WM performance.

*Keywords:* visual working memory, strategy, individual differences

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## Publications

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## Fields of Study

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## Introduction

Working memory (WM) is important to daily life, but the amount of information that we can actively hold at a given time is highly limited. A large number of studies have examined the extent to which various cognitive abilities contribute to WM performance. Specifically, individual differences in WM performance may reflect large variations in both storage capacity and attentional control ability (Cowan et al., 2006; Schor et al., 2020; Unsworth et al., 2014). Some have proposed that individuals vary in the size of mental storage space (Colom et al., 2006; Cowan et al., 2005; Mall et al., 2014). Others have emphasized the role of attentional control abilities in determining WM performance (Engle, 2002; Engle & Kane, 2003; Unsworth, Miller, et al., 2020). There is considerable evidence showing that WM performance relates to the ability to control access to WM (Fukuda et al., 2015; McNab & Klingberg, 2008; Robison et al., 2018; Vogel et al., 2005) or the ability to sustain attention over time (Adam et al., 2015; McVay & Kane, 2012; Unsworth, Robison, et al., 2020). Nevertheless, cognitive abilities such as storage capacity and attentional control may only partly explain WM performance.

Strategy use also drives important differences in WM performance. Studies have shown that explicit strategy instructions modulate WM performance (Atkinson et al., 2018; Bengson & Luck, 2016; Laine et al., 2018; Malinovitch et al., 2021; McNamara & Scott, 2001; Turley-Ames & Whitfield, 2003). In addition, work using strategy self-reports demonstrated large variability in strategy use across individuals (Bailey et al., 2008; Dunlosky & Kane, 2007; Morrison et al., 2016; Nicholls & English, 2020; Ridgeway, 2006; Waris et al., 2021). Given these findings, it is important to consider how strategy use varies across individuals instead of assuming that individuals all use the same strategies.

Despite growing interest in understanding strategy use, we still lack a clear understanding of how strategy choice influences WM performance. Individuals may employ a number of strategies, but it is unclear to what extent individuals use more beneficial strategies. Most studies exploring the relationship between strategy use and performance have focused on the verbal domain. In general, participants performed better when using more effective strategies, such as imagery or semantic strategies, compared to a rehearsal strategy (Bailey et al., 2008, 2011; Cokely et al., 2006; Dunlosky & Kane, 2007; McNamara & Scott, 2001). Although participants reported using a less effective rehearsal strategy most frequently, high-performing individuals were more likely to use effective strategies (Bailey et al., 2008, 2011; Kaakinen & Hyönä, 2007; McNamara & Scott, 2001; Turley-Ames & Whitfield, 2003; Unsworth, 2016; but see Unsworth & Spillers, 2010). In contrast, much less is known about how individuals choose different strategies to boost visual WM performance. Only a few studies have examined how strategy use in visual WM varies between groups and individuals. Some studies suggest that high-performing and low-performing individuals use different strategies (Cusack et al., 2009; Linke et al., 2011). In a similar vein, others have shown age-related differences in strategy use (R. Dai et al., 2018; Fiore et al., 2012; Nicholls & English, 2020).

One intuitive explanation for why individuals use different strategies is that strategy and ability are closely related. For example, individuals with high cognitive ability, such as visual WM capacity and fluid intelligence, may adopt encoding strategies that maximize behavioral performance (Cusack et al., 2009; Linke et al., 2011). Moreover, some studies have suggested that individuals with high WM ability are more likely to prioritize encoding of high-value items over low-value ones (Griffin et al., 2019; Robison & Unsworth, 2017; but see Elliott et al., 2020;

Mall et al., 2014). This idea is consistent with work showing that higher WM capacity is related to more effective strategy use in verbal WM or long-term memory (Bailey et al., 2008; Cokely et al., 2006; Schelble et al., 2012; Unsworth, 2016). Indeed, it is likely that effective strategies are more demanding, and that individuals with low cognitive ability are less able implement these strategies (Bailey et al., 2011; Turley-Ames & Whitfield, 2003).

Nonetheless, there are reasons to suspect that other factors may determine strategy choice. First, it is plausible that strategy selection depends on metacognitive awareness. Several recent studies suggest that individuals have good metacognitive knowledge on the effectiveness of strategies. When participants were allowed to construct visual displays to remember, they used grouping strategies to maximize performance (Magen & Berger-Mandelbaum, 2018; Magen & Emmanouil, 2019b, 2019a). Interestingly, some individuals may develop a more effective strategy over time, as shown by changes in both performance and strategy self-reports (Malinovitch et al., 2021). Further, providing explicit instructions on the effective strategies also largely improves WM performance (Malinovitch et al., 2021). More broadly, theoretical accounts of strategy selection in other cognitive domains have emphasized the importance of metacognitive and learning processes (Lieder & Griffiths, 2017; Rieskamp & Otto, 2006). Second, the role of task demands in strategy selection is largely underexplored. Recent studies suggest that, even without strategy instructions, we are able to adjust strategies according to different task demands (Cohen-Dallal et al., 2023; Donkin et al., 2016; Fougnie et al., 2016; Udale et al., 2018; van Lamsweerde et al., 2016). Yet, very few studies have explored how strategy choice depends on both individual and task factors (Cusack et al., 2009; Linke et al., 2011; Udale et al., 2018).

The current study investigated individual differences in optimal encoding strategy in visual working memory. Prior to proceeding, it is essential to operationally define optimality. Optimal behaviour in a broad sense can refer to what is worthwhile to the individuals themselves. For instance, individuals may simply choose the strategy that minimizes their cognitive effort, or choose to invest time and resources in other goals instead of the task at hand (Shenhav et al., 2017). Here we define the optimal strategy as the strategy that maximizes task performance (i.e., accuracy and/or response time). Indeed, to fully understand individual differences in strategy choice, it is necessary to identify the most beneficial strategy. However, little research has directly compared the effectiveness of encoding strategies in visual WM, and existing studies have provided mixed results (Atkinson et al., 2018; Bengson & Luck, 2016; Wang et al., 2020). To address this issue, we used a carefully designed task in which one specific strategy is objectively more optimal than other strategies. Our methodological approach is inspired by a visual search paradigm developed by our lab (Adaptive Choice Visual Search; Irons & Leber, 2016, 2018). This paradigm was designed to investigate how individuals choose attentional control strategies. There are two key features in this paradigm. First, participants are given the choice to search for one of the two available targets in the search display. Second, there is always one target that is more optimal (faster) to search for.

In three experiments, participants performed a flicker change detection task (Pailian et al., 2020; Pailian & Halberda, 2015; Rensink, 2000). Two displays (an original display and an altered version of the display) were repeatedly presented until participants localized a changing item (target). Importantly, each trial contained two targets (one red and one blue), and participants only had to report one target. Furthermore, the ratio of red to blue items varied from trial to trial. Therefore, to maximize performance, the optimal encoding strategy is to select/encode items in the smaller colour subset. We assessed individuals' strategy choice by measuring how frequently they selected the target within the smaller colour subset (optimal target). In Experiment 1, we examined whether individual differences in optimal encoding strategy may be explained by differences in ability. In Experiment 2, we further explored whether trait-like mechanisms support the use of different strategies. In Experiment 3, we used an instructional manipulation and open-ended reports to examine the extent to which explicit knowledge determines why some individuals would use the optimal strategy. In Experiment 4, we used a "one-shot" variant, in which memory displays are presented only once, to investigate the role of task demands in strategy use.

## Experiment 1

### Method

#### *Transparency and Openness*

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in all experiments. All data, analysis scripts, and experiment code are available at https://osf.io/jwrg4/. Data were analyzed with Matlab and RStudio (version 2021.09.1, R version 4.1.2). Experiment 1 was not preregistered.

#### *Participants*

Fifty participants (20 female, 30 male; mean age = 30.06 years; age range = 19 – 40 years) were recruited via Prolific (www.prolific.co) and received a compensation of $10/hr. All participants reported normal vision or corrected-to-normal vision and normal colour vision. All participants were located in the United States, had United States nationality, held a Prolific approval rating of at least 96%, and had at least 50 approved Prolific submissions prior to this experiment. The study was approved by The Ohio State University Institutional Review Board. All participants provided online informed consent before the study.

A power analysis using G*Power (Faul et al., 2007) showed that this sample size would provide 98% power for finding an effect of $r = .5$ or greater for all pairwise correlations.

We excluded participants whose accuracy was more than 2 *SD* below group mean on the flicker task (cutoff = 75.58%) and those who had a negative $K$ estimate on the WM capacity task. Four participants were excluded based on the criteria, leaving a final sample of 46.

### *General Procedure*

All experiments were programmed in Javascript and HTML Canvas. Surveys were collected using HTML forms. PHP was used to receive the data. All stimuli were presented against a light grey background. Participants completed the flicker change detection task, followed by the visual WM capacity task, in a single experimental session.

Participants were required to use a personal computer to perform the study. Since participants used their own devices, we are unable to provide the exact visual angle of the stimuli and instead report stimuli size in pixels. However, assuming that participants used a 24-inch monitor (1920 × 1080 screen resolution) at a viewing distance of 57 cm, 1° of visual angle would be equivalent to 36 pixels.

### *Flicker Change Detection Task*

Participants were asked to localize a change that occurred between two memory displays. Unlike the typical one-shot change detection task, the displays were repeated until participants reported a change (Nakashima & Yokosawa, 2011; Pailian et al., 2020; Pailian & Halberda, 2015; Rensink, 2000).

Each display consisted of nine oriented bars (length 60 pixels, width 15 pixels). There were an uneven number of red (RGB: 255, 0, 0) and blue (0, 0, 255) bars. On half of the trials, there were three red bars and six blue bars. On the other half, there were three blue bars and six red bars. These two trial types were randomized within each block. The orientations of bars were randomly sampled from a 180° circular space, with the constraint that any two bars would have a minimum angle difference of 15°. Stimuli locations were randomly selected within a 600 × 600-

pixel region around screen center with a minimum distance of 80 pixels between stimuli and a minimum horizontal distance of 80 pixels from the screen center.

The 2nd display was identical to the 1st display, except that two of the bars (targets) contained an orientation change (90° from the orientation in the 1st display). The targets were always one red bar and one blue bar.

The trial procedure is illustrated in Figure 1. At the start of each trial, a fixation cross was displayed for 500 ms and remained on screen throughout the trial. The 1st memory display was then presented for 500 ms, followed by a blank delay of 900 ms. Next, the 2nd memory display was presented for 500 ms, followed by another blank delay of 900 ms. The cycle of displays would be repeated until participants pressed the "F" key to indicate that they had found a target. Participants were allowed to make a response upon the first onset of the 2nd memory display, and they were instructed to press the key as soon as they found a target. Upon the keypress, the most recent memory display would be shown on screen, and participants responded by clicking on the location of an item. Finally, we provided feedback by showing "CORRECT" in green or "INCORRECT" in red.

In *choice blocks*, participants were free to select the blue or the red target to report. We explicitly told participants that each trial would contain two targets (one red and one blue), and that participants would only need to report one target per trial. Clicking on either the red or the blue target would be regarded as a correct response. Critically, we expected that the most optimal (fastest) strategy would be to remember items in the smaller colour subset and to report the target in that colour. Therefore, we refer to the target within the smaller colour subset as the optimal target, and the target within the larger colour subset as the non-optimal target.

In the *enforced-small block*, participants needed to determine which colour had fewer items in the display and to find the target in that colour (i.e., optimal target). This served as the control condition to confirm that participants were capable of enumerating items in the display and selectively focusing on the small colour subset.

Participants completed 240 trials. The first five blocks (200 trials) were *choice blocks*, and the last block (40 trials) was the *enforced-small block*. Five practice trials preceded the main task.

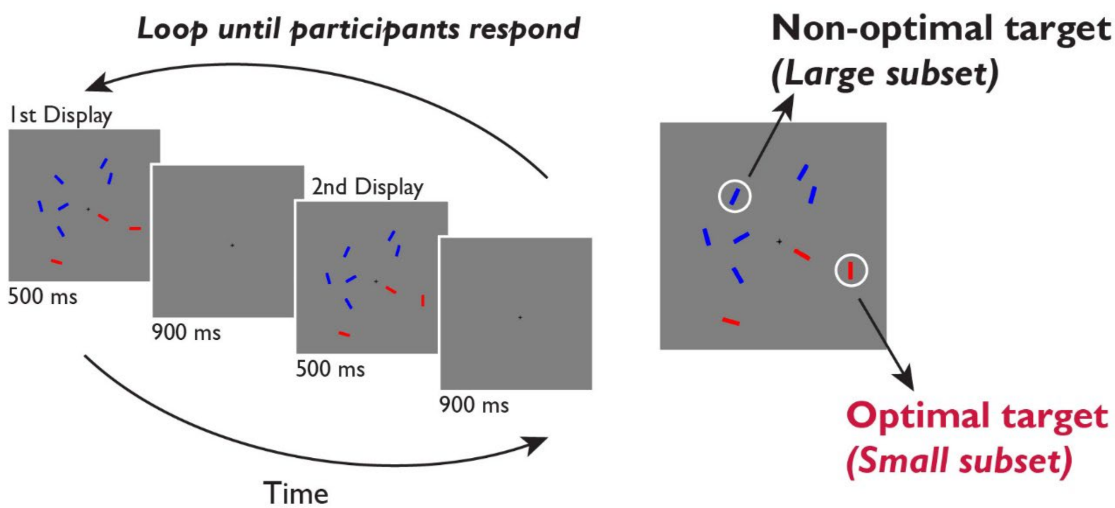


Figure 1. Trial Procedure of Flicker Change Detection Task. On each trial, two displays alternated until participants pressed “F” to indicate that they had found a changed item (target). Next, participants clicked on the location of a target and received accuracy feedback. There were always one blue and one red target, and participants were free to report either target. Moreover, half of the trials contained fewer red than blue items, and the other half contained fewer blue than red items. This makes it more optimal to encode items in the smaller colour subset and report the target in that colour (optimal target).

### ***Self-Reported Strategy Questionnaire***

After the *choice blocks*, participants completed a strategy questionnaire adapted from Irons and Leber (2018). Specifically, participants were asked to estimate the percentage of trials (0%, 20%, 40%, 60%, 80%, or 100%) in which they engaged in the following strategies: (a) searched for the color that had fewer items, (b) searched for one color for a long period of time (without switching to the other color), (c) searched for the color that had more items, (d) searched for the color that appeared first, (e) searched through items of both colors that had any change.

We first converted the strategy ratings to the percentage of the total sum of ratings. We then used these converted ratings to measure self-reported usage of optimal strategy, repeated strategy, and random strategy. Rating (a) was taken as a measure as optimal strategy, whereas rating (b) was classified as repeated strategy. The sum of ratings (c) and (d) were taken as a measure of random strategy. Following Irons and Leber, rating (e) was not used.

### ***WM Capacity Task***

We independently measured visual WM capacity in a colour change detection task (e.g. Luck & Vogel, 1997). Memory stimuli were 4 or 8 colored squares (45 × 45 pixels). These colours were randomly selected, without replacement, from nine distinct colours: red (255, 0, 0), green (0, 255, 0), blue (0, 0, 255), yellow (255, 255, 0), magenta (255, 0, 255), cyan (0, 255, 255), white (255 255 255), black (0, 0, 0), and orange (255, 128, 0). All squares were presented at randomly selected locations within a 600 × 600-pixel region around fixation, with the constraint that the center of each square was at least 72 pixels from the screen center (horizontal distance) and from any other square.

Each trial began with the presentation of a fixation cross for 1000 ms. The fixation cross remained on screen throughout the trial. Next, the memory stimuli were presented for 200 ms, followed by a delay of 900 ms. During the memory test, a coloured square appeared on screen, and participants had to press “Z” or “/” to indicate whether the colour was same or different as the square presented at that location. The test item had 50% probability of being a new colour (not presented during the memory array). Only accuracy was emphasized for the memory response. The following trial began immediately after the memory response was provided. Participants completed 120 trials (divided into 3 blocks). Trials were evenly divided between set sizes 4 and 8. Five practice trials preceded the experimental trials to familiarize participants with the task.

We transformed WM capacity task accuracy into a capacity estimate *(K)* using the standard formula (Cowan, 2001): $K = S \times (H - F)$. S is memory set size, H (hit rate) is the proportion of correct response to different probes, and F (false alarm) is the proportion of incorrect response to same probes. We calculated a *K* value for each set size and took the average to estimate each participant’s WM capacity.

**Results**

We measured accuracy and response times (RTs) to examine general performance on the flicker change detection task. In *choice blocks*, both the optimal target (small subset target) and non-optimal target (large subset target) were considered correct targets. Accuracy was high ($M$ = 93.96%), with participants reporting the optimal target on 68.17% of trials and the non-optimal target on 25.78% of trials.

In the *enforced-small block*, there were still two changed items (one in small subset, one in large subset), but only the optimal target was considered the correct target. Participants correctly identified the optimal target on 92.99% of trials. Errors in the *enforced-small block* were mostly due to participants' reporting an unchanged item (4.78% of trials) rather than the changed item in the large subset (2.23% of trials). In fact, 35 participants never reported the changed item in the large subset. A one-sample *t*-test also found that participants were not significantly more likely to report the changed item in the large subset, compared to the rate of reporting one unchanged item from the display (0.68%, which is 4.78% divided by 7 unchanged items), $t(45) = 1.62$, $p = .113$, 95% CI [.30, 4.15], $d_z = 0.24$. This suggests that most participants complied with task instructions and rarely misreported the change in the large colour subset.

RTs were timed from the onset of the 1st display until participants made a response to stop the loop of displays. The total duration of each loop (the two displays and blank delays in between) was 2800 ms. Trials with incorrect responses (6.2%) and trials with RTs more than 2 *SD* from the participant mean (3.88%) were excluded from analysis of RTs. Mean RTs were 3002 ms in the *choice blocks* and 2590 ms in the *enforced-small block*.

***Individual Differences***

Our individual differences analysis focused on measures from the *choice blocks*, in which participants were given the choice to report the red target or the blue target. For all individual differences measures (optimality rate, switch rate, and self-reported strategy ratings), participants were identified as univariate outliers if the z-score exceeds +/−3.29 ($p < .001$). For correlations, participants with a Mahalanobis distance more than 13.82 ($p < .001$) were regarded as multivariate outliers.

**Strategy use.** To assess strategy use, we measured optimality rate, which is the proportion of trials in which participants reported the optimal target (small subset target). As shown in Figure 2a, optimality rate was bimodally distributed ($M$ = 68.17%, $SD$ = 22.12%, range = 38.5 – 99.5%). Some participants almost always reported the optimal target (approaching 100%), and many others reporting the optimal target and the non-optimal target equally often (around 50%). This suggests that strategy use was far from optimal, and that there were large differences in strategy use across individuals. A critical assumption of our task is that it is more optimal to look for the optimal target. To verify this, we examined the correlation between optimality rate and flicker task RTs (Figure 2b). We found that those who chose the optimal target more frequently were faster in finding the target, $r = -.56$, $t(44) = 4.53$, $p < .001$, 95% CI [– .73, – .33]. This confirms our assumption that it is a more optimal strategy to remember items from the smaller colour subset.

As a control analysis, we examined whether the relationship between optimality and RTs could be driven by a third variable, such as the general tendency to perform fast. If so, we should also find a difference in speed between optimal and sub-optimal participants when they all use the optimal strategy. However, we found no significant correlation between optimality rate and RTs on the *enforced-small block,* $r = -.25$, $t(44) = 1.71$, $p = .094$, 95% CI [– .50, .04]. Further, we used Dunn & Clark's $z$ tests to compare the two correlations (Diedenhofen & Musch, 2015; Dunn & Clark, 1969). The correlation between optimality and *choice block* RT was significantly stronger than the correlation between optimality and *enforced block* RT, $z = -3.86$, $p < .001$. Therefore, individual differences in the tendency to perform quickly are not the prime determinant in the use of optimal strategy.

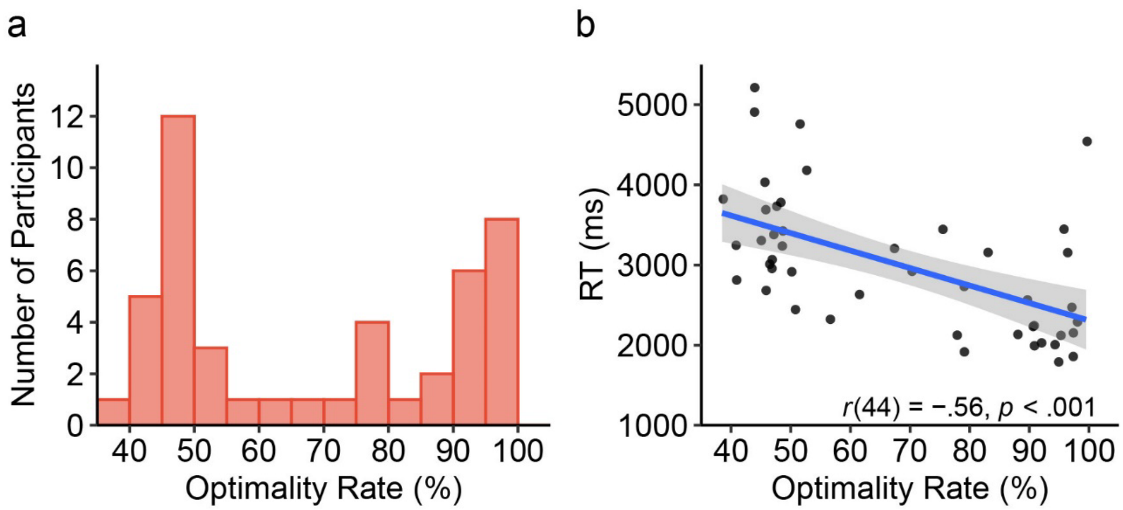


Figure 2. Individual Differences in Strategy Optimality in Experiment 1. a) The histogram shows the distribution in optimality rate (percent of optimal target choice). b) The scatterplot (with best-fitting regression line) showing the relationship between optimality rate and RT.

**Switch rate.** Next, we examined participants' switch rate (i.e., whether the target colour reported on trial *n* is the same as that on trial *n – 1*). Switch rate varied between 1.03% and 59.49% ($M$ = 46.73%, $SD$ = 8.81). Most participants switched frequently between the two colours. We identified one univariate outlier in switch rate (1.03%, *z* score = –5.19)**.** Switch rate was positively correlated with optimality rate both when the outlier was included, $r$ = .40, $t(44)$ = 2.86, $p$ = .006, 95% CI [.12, .62], and when the outlier was excluded, $r$ = .47, $t(43)$ = 3.51, $p$ = .001, 95% CI [.21, .67]. Note that participants using the optimal encoding strategy should switch around 50% of trials. It is likely that some participants switched less often than required to be optimal.

**Self-reported strategy questionnaire.** We also examined how self-reported strategy correlated with optimality rate and switch rate. Qualitative conclusions do not change regardless of whether we include or exclude the univariate outlier in switch rate. When multiple comparisons were reported, we used Holm-Bonferroni correction to control for family-wise error rate (Holm, 1979).

We found that self-reported optimal strategy significantly predicts optimality rate in the task, $r = .79$, $t(44) = 8.54$, $p_{\mathrm{HB}} < .001$, 95% CI [.65, .88]. This suggests that participants have good metacognition of their strategy use. Self-reported optimal strategy was correlated with switch rate both when we include the outlier, $r = .33$, $t(44) = 2.35$, $p_{\mathrm{HB}} = .024$, 95% CI [.05, .57], or exclude the outlier, $r = .51$, $t(43) = 3.86$, $p_{\mathrm{HB}} < .001$, 95% CI [.25, .70].

Self-reported repeated strategy did not correlate with optimality rate, $r = -.01$, $t(44) = 0.05$, $p_{\mathrm{HB}} = .964$, 95% CI [−.30, .28]. Interestingly, we did not find evidence that self-reported repeated strategy was correlated with switch rate both with the outlier, $r = -.26$, $t(44) = 1.81$, $p_{\mathrm{HB}} = .153$, 95% CI [−.51, .03], and without the outlier, $r = -.13$, $t(43) = 0.84$, $p_{\mathrm{HB}} = .808$, 95% CI [−.41, .17]. This might be because only a few participants reported using the repeated strategy frequently, and that most participants switched between reporting red and blue items fairly often.

Self-reported random strategy was negatively correlated with optimality rate, $r = -.50$, $t(44) = 3.88$, $p_{\mathrm{HB}} < .001$, 95% CI [−.69, −.25]. However, self-reported random strategy did not correlate with switch rate both including the outlier, $r = -.03$, $t(44) = 0.23$, $p_{\mathrm{HB}} = .818$, 95% CI [−.32, .26], and excluding the outlier, $r = -.18$, $t(43) = 1.22$, $p_{\mathrm{HB}} = .230$, 95% CI [−.45, .12].

**WM Capacity.** Average WM capacity ($K$) measured independently from the colour change detection task is 2.76 (ranging from 0.4 to 4.4). We found that individuals with high WM capacity also showed higher accuracy on the flicker task, $r = .49$, $t(44) = 3.76$, $p < .001$, 95% CI [.24, .69], but WM capacity was not correlated with RTs, $r = -.05$, $t(44) = 0.30$, $p = .762$, 95% CI [− .33, .25]. Thus, there is some evidence that WM capacity can predict general performance on the flicker task (see also Pailian et al., 2020; Pailian & Halberda, 2015).

The critical question is whether strategy use can be explained by differences in ability. We found no correlation between WM capacity and optimality rate (Figure 3), $r = -.08$, $t(44) = 0.57$, $p = .575$, 95% CI [−.37, .21]. This finding might seem surprising when considering previous work suggesting that high-performing individuals also use more effective encoding strategies in WM (e.g., Cusack et al., 2009; Linke et al., 2011). Nevertheless, our results are consistent with related work in visual search showing no relationship between ability and strategy (Irons & Leber, 2016).

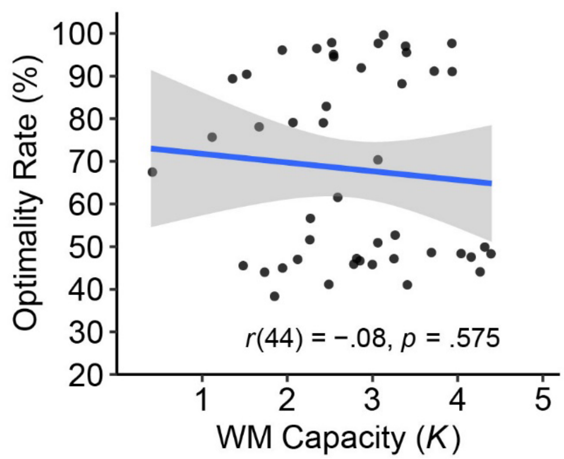


Figure 3. Correlation between WM Capacity and Strategy Optimality. The scatterplot (with best-fitting regression line) showing the relationship between WM capacity ($K$), measured with a change detection task, and optimality rate on the flicker task.

## Discussion

Experiment 1 found that individuals often use sub-optimal encoding strategies in visual WM. Even though it was generally faster to find the optimal target, participants did not always choose to report this target. Moreover, individuals who reported using the optimal encoding strategy also chose the optimal target more frequently, indicating that they had good metacognitive knowledge on strategy use. This is in line with related work in visual search showing that participants have good insight into the strategies they used (Irons & Leber, 2018). Importantly, while memory performance depends on both ability and strategy, individual differences in optimal strategy use seem to be largely independent of ability. These findings are largely inconsistent with the idea that ability may explain differences in strategy use and instead suggest that other factors determine strategy choice. It is worth noting that work in related fields suggests that strategy use is a stable cognitive trait independent of ability. For example, visual search studies have shown that optimal attentional control strategies do not correlate with cognitive ability, such as WM capacity and visual search ability (Irons & Leber, 2016, 2020; McKinney et al., 2023). Likewise, work has found that cognitive ability does not determine strategic criterion shifting in recognition tasks (Miller & Kantner, 2020).

## Experiment 2

In Experiment 2, we further examined whether trait-like mechanisms underlie individual differences in optimal encoding strategy. Although we observed individual differences in strategy use in Experiment 1, it is unclear whether individuals would demonstrate consistency in strategy use over time. To examine this, we asked participants to perform the flicker task on two separate days. On the one hand, it seems reasonable to assume that there are stable individual differences in strategy use, since related work in visual search has shown good test-retest reliability in strategy use (Clarke et al., 2022; Irons & Leber, 2018). On the other hand, recent work suggests that some individuals demonstrate learning and discovery of an alternative, better strategy in WM over time (Malinovitch et al., 2021). This raises the possibility that individual differences in strategy use reflect differences in learning rate.

### Method

The study was preregistered before data collection with all details of the method and analyses (https://osf.io/4m8hd). All analyses not included in the preregistration plan are declared as exploratory.

#### *Participants*

Fifty participants (25 female, 24 male, 1 other; mean age = 29.62 years; age range = 19 – 40 years) on Prolific took part in two 45-min sessions on two separate days. They received a compensation of $10/hr and a completion bonus of $3.75. Three of these participants have also participated in Experiment 1.

Two additional participants took part in Session 1 but did not complete Session 2. Their data were excluded from the analysis. Of the 50 participants who completed both experimental sessions, two were excluded based on our preregistered exclusion criterion (overall accuracy more than 2 *SD* below group mean, cutoff = 83.54%). Therefore, 48 participants were included in the final analysis.

### *General Procedure*

The two experimental sessions were separated by at least 1 day but not more than 7 days. For each session, participants performed 320 trials (8 blocks) of the flicker memory task. Here we only included *choice blocks*, in which participants could choose to report the optimal or the non-optimal target. Participants were given 5 practice trials at the start of each session to familiarize themselves with the task. At the end of the second session, they completed the strategy questionnaire used in Experiment 1.

## Results

Flicker task accuracy was high in both sessions (Session 1 $M = 94.56\%$, $SD = 5.27\%$; Session 2 $M = 95.65\%$, $SD = 4.24\%$). Trials with incorrect responses (4.90%) and trials with RTs more than 2 *SD* from the participant mean (3.82%) were excluded from analysis of RTs. Mean RTs were 3084 ms in Session 1 and 2788 ms in Session 2.

### *Individual Differences*

As in Experiment 1, individual differences measures, including optimality rate, switch rate, and self-reported strategy ratings, were screened for univariate outliers (*z*-score exceeding +/−3.29) and bivariate outliers (Mahalanobis distance > 13.82).

**Optimality rate.** There was considerable variation in optimality rate. Optimal target choice varied between 34.69% and 99.38% ($M = 78.51\%$, $SD = 20.44\%$). As in experiment 1, we found that optimality rate was associated with faster RTs, $r = -.62$, $t(46) = 5.37$, $p < .001$ , 95% CI [−.77, −.41].

We further assessed internal consistency of optimality rate using split-half reliability with a Spearman-Brown correction, averaged over 5000 random splits (Parsons et al., 2019). Results showed high consistency for optimality rate ($r = .99$ in both Session 1 and Session 2). To assess consistency of strategy across sessions, we examined test-retest reliability of optimality rate with Pearson's correlation coefficients. Optimality rate was highly correlated between the two sessions, $r = .80$, $t(46) = 8.95$, $p < .001$ , 95% CI [.66, .88]. However, as shown in Figure 4, many participants reported the optimal target more frequently on Session 2 ($M$ = 81.91%) compared to Session 1 ($M$ = 75.1%). This is in contrast to work showing that visual search strategy use is largely consistent within the same individuals (Clarke et al., 2022; Irons & Leber, 2018).

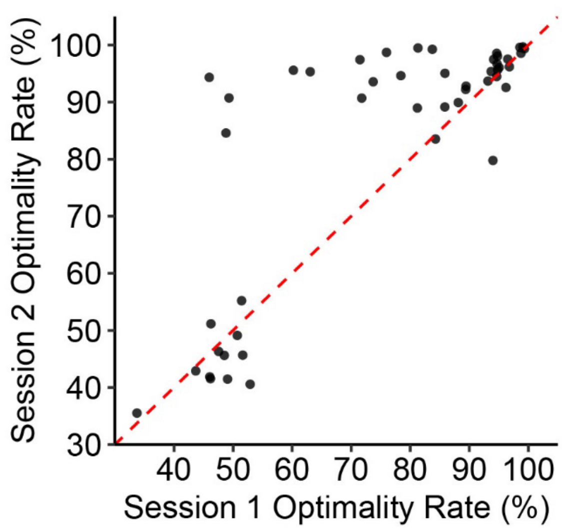


Figure 4. Strategy Optimality across Sessions in Experiment 2. The scatterplot showing strategy optimality across sessions. The red dotted line represents perfect test-retest reliability.

**Exploratory analysis.** To further examine these large changes in strategy use, we conducted exploratory analysis on optimality rate for each block (40 trials). Specifically, we looked at the learning curves at the individual level (Figure 5). This would provide insight into whether the strategy change was due to a gradual improvement or a sudden discovery of the optimal strategy (Malinovitch et al., 2021; Nowakowska et al., 2021; Wynton & Anglim, 2017). Our analysis focused only on correct trials to exclude any potential changes in accuracy due to practice or fluctuations in performance over time. We found that some participants were consistently optimal (at least 80%) or sub-optimal (around 50%) in all blocks. Notably, many participants performed at chance-level optimality at the start of the experiment but later showed a sharp increase in optimality rate, after which they remained at ceiling-level optimality. There is large variability in when this sharp increase occurs. Some participants switched to the optimal strategy within the first few blocks. The pattern we observed here is more consistent with a sudden discovery of strategy rather than a gradual improvement of strategy use.

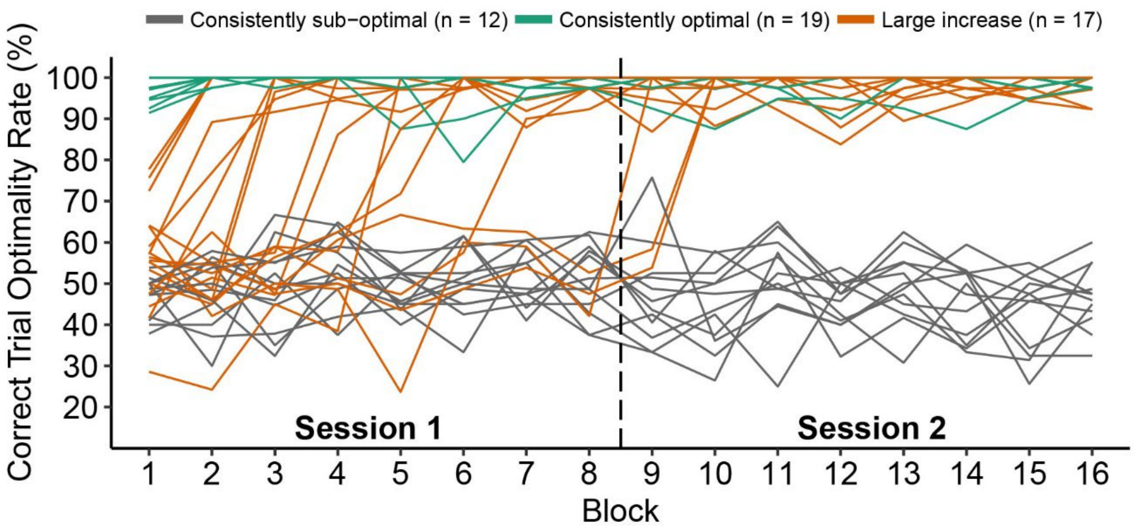


Figure 5. Exploratory Timecourse Analysis in Experiment 2. Individual learning curves as a function of block number. The black dotted line indicates the session break (1 to 7 days). The grey lines represent participants who used sub-optimal strategies throughout the experiment (around 50%), whereas the green lines represent participants who used optimal strategies since the first block (optimality >= 80%). The orange lines represent participants using sub-optimal strategies at first but later switched to the optimal strategy.

**Switch rate.** Participants switched frequently between the two colours (*M* = 49.85%, *SD* = 2.45%, range= 42.15% – 54.97%). Similar to Experiment 1, optimality rate was positively correlated with switch rate, $r = .36$, $t(46) = 2.59$, $p = .013$, 95% CI [.08, .58]. However, we did not see strong evidence for consistency of switching frequency. Split-half reliability for switch rate was low ($r = .06$ in Session 1 and $r = .22$ in Session 2), and test-retest reliability across sessions was marginally significant, $r = .28$, $t(46) = 2.01$ , $p = .0504$, 95% CI [.00, .53].

**Self-reported strategy questionnaire.** Here we also examined whether participants have good metacognitive insight on the strategies they used. Self-reported optimal strategy was correlated with higher optimality rate, $r = .78$, $t(46) = 8.53$ , $p_{\mathrm{HB}} < .001$, 95% CI [.64, .87], and higher switch rate, $r = .32$, $t(46) = 2.31$, $p_{\mathrm{HB}} = .026$, 95% CI [.04, .56].

Self-reported repeated strategy did not correlate with either optimality rate, $r = -.20$, $t(46) = 1.39$, $p_{\mathrm{HB}} = .340$, 95% CI [−.46, .09], or switch rate, $r = -.11$ , $t(46) = 0.72$ , $p_{\mathrm{HB}} = .473$, 95% CI [−.38, .18].

Self-reported random strategy was correlated with lower optimality rate, $r = -.50$, $t(46) = 3.89$, $p_{\mathrm{HB}} < .001$, 95% CI [−.68, −.25], but not correlated with switch rate, $r = -.09$ , $t(46) = 0.59$, $p_{\mathrm{HB}} = .561$, 95% CI [−.36, .20]. As in Experiment 1, both higher ratings on optimal strategy and lower ratings on random strategy predicted more optimal target choices.

## Discussion

Experiment 2 explored whether individual differences in strategy use reflect stable cognitive traits. We replicated Experiment 1 in showing that individuals often use sub-optimal encoding strategies. Interestingly, some participants showed large changes in strategy optimality across sessions. These findings diverge from work showing that there are stable individual differences in visual search strategies (Clarke et al., 2022; Irons & Leber, 2018). An exploratory analysis further revealed that many participants showed a sudden, large increase in optimal target choice, suggesting that there is learning and discovery of the optimal strategy (Malinovitch et al., 2021). Moreover, the finding that this strategy change occurred early during the task is consistent with previous work showing that participants change their strategies most frequently during the first few blocks or first few sessions (Fellman et al., 2020; Waris et al., 2021).

## Experiment 3

Experiment 2 showed that many participants switched to the optimal encoding strategy during the experiment. Moreover, participants had good metacognitive insight into the strategies they used. A straightforward interpretation of these results is that participants demonstrating a strategy change discovered the optimal strategy at variable timepoints, whereas participants using sub-optimal strategies remained unaware of the best strategy (e.g., Malinovitch et al., 2021; Schuck et al., 2015). However, we cannot rule out other explanations. For example, related work in visual search suggests that effort avoidance is an important determinant of strategy use. By this account, participants using sub-optimal strategies are aware of the optimal strategy but are simply unwilling to use it (Irons & Leber, 2018; Zhang et al., in prep).

Here we examined the relationship between explicit knowledge and the use of optimal encoding strategy. First, we used open-ended strategy reports to assess the participants' explicit knowledge of the optimal strategy. Second, we tested whether strategy recommendations motivate participants to adopt the optimal encoding strategy. If explicit awareness determines strategy use, we should observe a positive relationship between awareness and strategy use in the absence of strategy recommendations. Additionally, participants should be more likely to use optimal strategies after receiving recommendations on the best strategy.

### Method

The study was preregistered before data collection with all details of the method and analyses (https://osf.io/5jw4h).

### ***Participants***

One hundred students (61 female, 38 male, 1 other; mean age = 18.83 years; age range = 18 – 32 years) at The Ohio State University participated in the experiment for course credit. All participants reported normal vision or corrected-to-normal vision and normal colour vision. Participants were randomly assigned to the no-instruction group or the instruction group (50 in each group).

Although we used a sample size of 50 for Experiments 1 and 2, we decided to double the sample size in Experiment 3 since we would use a between-subjects design. A sample size of 100 should provide >99% power for finding an effect of $r = .5$ for all pairwise correlations. Moreover, we aimed to use a mixed ANOVA to compare performance across groups and time. Anticipating that we would obtain an effect of $f = .25$ for the interaction, we would require at least 46 participants in total to achieve 90% power.

Eight participants (5 in no-instruction group, 3 in instruction group) were excluded due to low performance (accuracy below 2 *SD* from the mean of all participants).

### ***Procedure***

Here we used a pretest-posttest design to examine the effects of a between-subjects instruction manipulation. The main experiment contained 320 test trials: 200 trials in the pretest phase and 120 trials in the posttest phase. Each test block contained 40 trials, and a practice block of 5 practice trials preceded the main experiment. The pretest phase was identical to the *choice blocks* in previous experiments. Participants could choose to report the red or blue target on each trial, and we did not provide any information on the optimal encoding strategy to either group.

Following the pretest phase, participants in both instruction and no-instruction groups completed an open-ended questionnaire examining their explicit knowledge of the optimal encoding strategy: 1) “Could you describe the best strategy to perform the task (fastest way of finding the changed item)?” and 2) “What is the strategy you used most often?”

Next, participants in the instruction group received strategy instructions about the optimal strategy before they proceeded to the posttest phase. We explicitly told participants that the best strategy is to remember items in the small colour subset. In contrast, participants in the no-instruction group did not receive any strategy instructions.

At the end of the experiment, participants in the no-instruction group completed an additional questionnaire (adpated from Schuck et al., 2015). We assessed their awareness of the subset size difference with the following questions: 1) “Are you aware that in some displays, there were fewer red than blue items, and in other displays, there were fewer blue than red items?” [yes/no] and 2) “Did you use this information to perform the task?” [yes/no]. If participants responded “yes" to question 2, they were further asked to report the percentage of time (0%, 20%, 40%, 60%, 80%, 100%) they used the optimal encoding strategy: 3) “One way to do this task is to remember whichever color has the smaller number of items. For example, if there are 3 red and 6 blue items, you would choose to remember the red ones. Did you ever use this strategy? If so, please report the percentage of time you used it (out of 100).”

**Results**

Overall accuracy was 91.42% (*SD* = 7.94). For analysis of RTs, we excluded incorrect trials and RTs more than 2 *SD* from the participant mean (3.67% of trials). Mean correct RT was 3267 ms.

To examine performance across conditions, we submitted accuracy and RTs to a 2 × 2 mixed ANOVA with instruction group (instruction, no-instruction) as a between-subjects factor and time (pretest, posttest) as a within-subjects factor. Accuracy did not differ between instruction (90.63%) and no-instruction groups (92.68%), $F(1,90) = 1.60$, $p = .209$, $\eta_p^2 = .017$. Accuracy improved from pretest (90.82%) to posttest (92.48%), $F(1,90) = 8.60$, $p = .004$, $\eta_p^2 = .087$. There was an interaction between group and time, $F(1,90) = 3.96$, $p = .050$, $\eta_p^2 = .042$, showing that instruction group improved more in accuracy compared to the no-instruction group (2.79% vs. 0.53%).

For RTs, there was no significant difference between instruction (3107 ms) and no-instruction groups (3309 ms), $F(1,90) = 0.84$, $p = .363$, $\eta_p^2 = .009$. There was a main effect of time, $F(1,90) = 130.01$, $p < .001$, $\eta_p^2 = .591$, showing that RTs were faster in posttest (2921 ms) compared to pretest (3495 ms). The interaction between group and time did not reach significance, $F(1,90) = 3.89$, $p = .052$, $\eta_p^2 = .041$, but the numerical trend was towards a larger decrease in RT for the instruction group (672 ms) compared to the no-instruction group (474 ms). We did not expect any systematic differences in performance in the pretest phase. We expected instructions to have minimal impact on accuracy, but if people switched to the optimal strategy, there should be a corresponding drop in RT.

***Strategy Use***

We first assessed strategy use in the pretest phase, when participants in both the instruction and no-instruction groups did not receive explicit instructions on the best strategy. As in previous experiments, we found that optimality rate was bimodally distributed ($M = 61.14\%$, *SD* = 20.35, ranging from 31% to 100%). We found that higher optimality rate was correlated with faster RTs, $r = -.27$, $t(90) = 2.71$, $p = .008$, 95% CI [−.45, −.07].

Results also showed that most participants switched frequently between red and blue items ($M = 47.78\%$, $SD = 8.56$). Two participants were identified as univariate outliers because they switched infrequently (5.64%, *z*-score = − 4.92) or very frequently (86.67%, *z*-score = 4.54). We did not find a significant correlation between optimality and switch rate when including the outliers, $r = .12$, $t(90) = 1.17$, $p = .247$, 95% CI [−.09, .32], or excluding the outliers, $r = .17$, $t(88) = 1.66$, $p = .102$, 95% CI [−.03, .37].

***Strategy Instructions***

Optimality across conditions was illustrated in Figure 6. To examine effects of strategy instructions, we analyzed optimality rate with a 2 (group) × 2 (time) mixed ANOVA. We found no main effect of group, $F(1,90) = 0.34$, $p = .559$, $\eta_p^2 = .004$, showing no systematic differences between instruction (69.73%) and no-instruction groups (67.38%). There was a main effect of time, $F(1,90) = 66.83$, $p < .001$, $\eta_p^2 = .426$, indicating that participants were generally more optimal during posttest (75.91%) compared to pretest (61.20%). Importantly, we found an interaction between group and time, $F(1,90) = 22.78$, $p < .001$, $\eta_p^2 = .202$, suggesting a larger increase in optimality from pretest to posttest in the instruction group (23.3%), compared to the no-instruction group (6.12%). Finding a small increase in the no-instruction group is consistent with the idea that participants would start using optimal encoding strategies after discovering this strategy at variable timepoints. Critically, the improvement in the instruction group is above and beyond these spontaneous strategy changes over time.

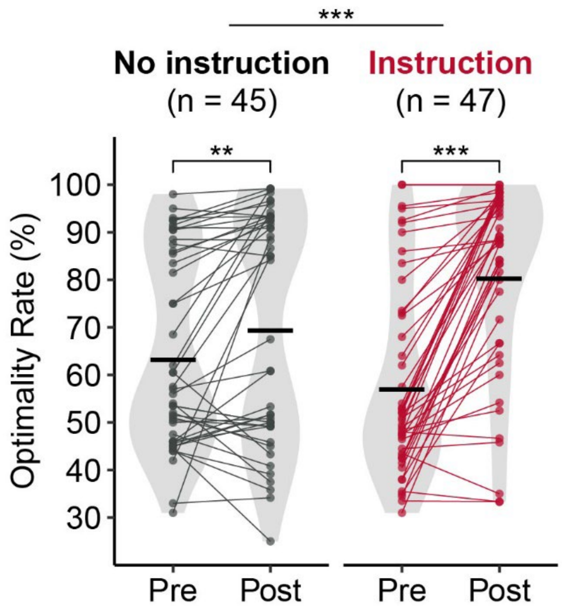


Figure 6. Pretest-Posttest Strategy Optimality by Instruction Group. Participants were randomly assigned to the no-instruction group (n = 45) or the instruction group (n = 47). In the pretest phase, no strategy instructions were provided. Before the posttest phase, the instruction group received explicit instructions on the best strategy, while participants in the no-instruction group did not receive any strategy instructions. The violin plots represent the distribution of data. The thick horizontal bars indicate the mean for each condition. The data points represent individual participants, and the thin lines connect each participant's pretest and posttest optimality.

Furthermore, we predicted that providing strategy recommendations would have a much stronger impact on participants who never used the optimal strategy during pretest, compared to those who already started using the optimal strategy. Therefore, to examine the effects of strategy instructions more closely, we conducted a follow-up analysis after excluding participants who have already adopted the optimal strategy by the end of the pretest phase. Our exploratory analysis from Experiment 2 suggests that participants either perform at chance-level optimality (50%) throughout the experiment, are highly optimal starting from the first block, or remain at ceiling optimality after switching to the optimal strategy. Here we examined block-by-block optimality to identify whether participants are using the optimal strategy: those who started adopting the optimal strategy (maximum block optimality >= 80%) by the end of the pretest phase (optimal group) and those who never used the optimal strategy (sub-optimal group). This analysis was restricted to trials with correct responses (correct trial optimality rate) to reduce noise due to changes in accuracy. Based on this analysis, we classified 43 participants into the optimal group (mean optimality = 78.95%) and 49 participants into the sub-optimal group (45.5%). In the sub-optimal group, there were 22 participants from the no-instruction group and 27 participants from the instruction group.

We analyzed optimality rate of the sub-optimal group using a 2 (group) × 2 (time) mixed ANOVA. There was both a main effect of group, $F(1,47) = 12.41$, $p < .001$, $\eta_p^2 = .209$, and a main effect of time, $F(1, 47) = 36.08$, $p < .001$, $\eta_p^2 = .434$. This indicates that the instruction group (59.07%) was more optimal than the no-instruction group (48.56%), and that participants became more optimal in the posttest phase (61.99%) compared to pretest (45.63%). Critically, there was an interaction, $F(1,47) = 23.14$, $p < .001$, $\eta_p^2 = .330$, suggesting that sub-optimal participants in the instruction group improved more compared to those in the no-instruction group (29.5% vs. 3.26%). This analysis provides further evidence that explicit knowledge motivates use of the optimal encoding strategy.

***Awareness***

We classified participants as being aware of the optimal strategy if they indicated that the best strategy is to select/encode items in the small subset, or to find the target in the small subset. Based on this criterion, 45 participants (25 in the no-instruction group and 20 in instruction group) were classified as being aware of the optimal strategy, and 47 participants (20 in no-instruction group, 27 in instruction group) were unaware of the optimal strategy. A two-sample *t*-test found that those who were aware of the optimal strategy were more optimal than those who were unaware (75.6% vs. 47.2%), $t(90) = 9.34$, $p < .001$, 95% CI [22.4, 34.4], $d_s = 1.95$. The results were illustrated in Figure 7. This supports the idea that explicit awareness is important for strategy use.

We also examined whether participants' most often used strategy is the same as the self-reported best strategy. For the aware group, 40 participants used their self-reported best strategy (i.e., optimal strategy) most often, and 5 participants reported using other strategies most often. For the unaware group, 34 participants used their self-reported best strategy most often, while 13 participants reported using other strategies most often.

Participants in the no-instruction group completed an additional questionnaire at the end of the experiment. Almost all participants (44 out of 45) reported awareness of the small versus large colour subsets in the display. In addition, 38 participants reported using the subset size difference to perform the task. Finally, as in previous experiments, there is large variability in self-reported ratings on how often they used the optimal strategy ($M$ = 79.47%, $SD$ = 23.01%).

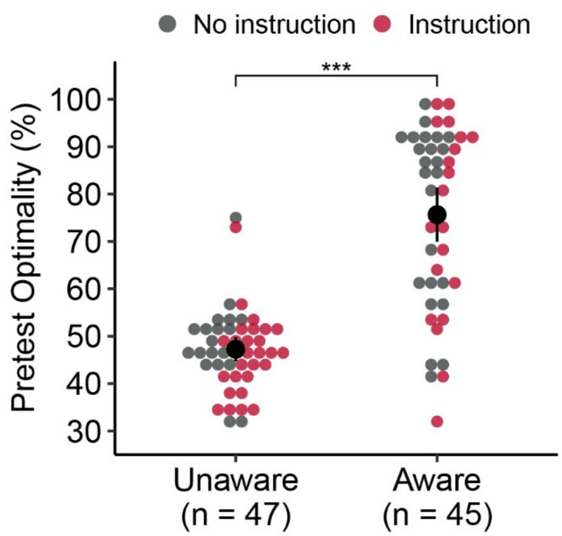


Figure 7. Awareness of the Optimal Strategy. Participants were classified as unaware (n = 47) or aware (n =45) of the optimal strategy based on their responses on the open-ended strategy report. The black dots represent the mean for each group, and the error bars represent 95% confidence intervals. Each coloured dot represents a participant.

## Discussion

The goal of Experiment 3 was to examine whether the observed strategy change reflects discovery of the optimal encoding strategy. As expected, we found that providing explicit instructions on the optimal strategy led to a sudden, large increase in optimal target choice. The pretest-posttest change in the instruction group cannot simply be attributed to the stabilization of a previously discovered strategy. First, only a few participants in the no-instruction group showed improvement during the posttest phase. Second, we confirmed that many individuals using sub-optimal strategies during the pretest phase switched to the optimal strategy after receiving strategy instructions. Moreover, open-ended strategy reports showed that participants who reported awareness of the optimal strategy were more optimal. Therefore, it seems more likely that the use of sub-optimal strategies is due to the ignorance of the optimal strategy, rather than other explanations, such as avoidance of cognitive demands (cf. Zhang et al., in prep). Taken together, these results suggest that explicit awareness plays a key role in visual WM strategy use.

It is important to note that the current study was not designed to examine the directionality of awareness and strategy change (see Schunn et al., 2001, for a discussion). On the one hand, it is possible that awareness of the optimal strategy precedes the strategy change. On the other hand, participants may have become aware of the optimal strategy after incidentally using this strategy. Moreover, the distinction between explicit and implicit knowledge is worth discussing. Our findings are consistent with the view that people can use explicit knowledge about statistical regularities to improve WM performance (Ngiam et al., 2019). However, implicit knowledge may also guide encoding and storage of information into WM. Several studies have manipulated change probability in a change detection task such that changes were more likely to occur in a certain location (Beck et al., 2008; Umemoto et al., 2010). These studies found that participants were more likely to detect high probable changes compared to low probable changes. Interestingly, although some participants were explicitly aware of the location probability manipulation, unaware participants in these studies still showed a bias toward high probable locations. This might suggest that explicit knowledge is not required for learning of probability information. Nevertheless, other work has suggested that participants who have explicit knowledge of the probability manipulation are more likely to use optimal strategies (Beck et al., 2018). Further work is needed to examine the interaction between explicit and implicit learning.

## Experiment 4

In previous experiments, we found large individual differences in optimal encoding strategy. However, it remains unclear how task demands modulate individual differences in encoding strategies. Several studies have suggested that participants use different encoding strategies depending on task expectations (Cohen-Dallal et al., 2023; Donkin et al., 2016; Fougnie et al., 2016; van Lamsweerde et al., 2016; Wyble et al., 2019). For example, Cohen-Dallal et al. (2022) manipulated the probability of different task types in different test sessions and found that participants encode items more precisely and fixate on more items when expecting a continuous report task, compared to when they expect a change detection task. Similarly, Fougnie et al. (2016) showed that changing the number of items participants have to report in a continuous report task also influences how precisely participants encode items. Importantly, some individuals may be more likely to adapt or change strategies depending on the task context (Schunn & Reder, 2001). Linke et al. (2011) argues that participants tend to use similar encoding strategies in a whole report task, where participants have to report the identity of memory items. In contrast, individuals vary in their encoding strategies in the change detection task, with low-performing individuals more likely to use sub-optimal encoding strategies (see also Cusack et al., 2009). Therefore, features of a task may encourage or discourage the use of certain strategies, and this effect may be more pronounced for some individuals.

Our task might have unintentionally encouraged participants to use sub-optimal strategies. Specifically, the flicker paradigm allowed participants to repeatedly view and encode the displays, and the majority of participants were able to perform at ceiling accuracy regardless of whether they used the optimal strategy. Yet, using the optimal encoding strategy leads to large improvements in response speed. Our instructions emphasized speed, and we assumed that the self-paced procedure would motivate participants to find the target as quickly as possible. However, since we only provided accuracy feedback in our task, it is possible that participants were less sensitive to performance benefits in response speed compared to accuracy. If this is the case, then we should expect individuals to choose the optimal strategy when it maximizes their task accuracy. Experiment 4 tested this possibility by increasing task difficulty. The task design was similar to previous experiments, except that the displays were presented only once (i.e., one-shot paradigm; Pailian & Halberda, 2015; Zhao et al., 2022). Compared to the flicker paradigm, the one-shot paradigm places a premium on accuracy. Even though it is difficult to localize the target in a 9-item display, participants will be better able to achieve high accuracy if they use the optimal strategy of encoding only the small colour subset.

**Method**

The study was preregistered before data collection with all details of the method and analyses (https://osf.io/u8f6k). All analyses not included in the preregistration plan are declared as exploratory.

***Participants***

Fifty new participants (10 female, 39 male, 1 other; mean age = 29.54 years; age range = 19 – 40 years) were recruited on Prolific. Here we planned to compare results between this experiment (one-shot task) and Experiment 1 (flicker task). Thus, we used a bootstrap resampling procedure (Strong & Alvarez, 2019) to create power simulations based on results from Experiment 2. In this simulation, we assumed that participants would choose to report the optimal target more frequently in the one-shot task than in the flicker task. First, we identified participants who reached ceiling performance (> 90% optimality) on at least one of the blocks (overall mean optimality = 89.3%). Second, we randomly sampled 50 participants (with replacement) from this group of highly optimal participants. Next, we randomly selected 200 trials for each participant (with replacement). We then compared the optimality rate of this simulated set with that of Experiment 1, calculating the effect size ($d_s$) and using a two-sample *t*-test. After repeating this procedure 100,000 times, we found a mean effect size of $d_s = 1.28$ and a power of 100% (i.e., all simulated comparisons reached significance in the predicted direction). Further, with a sample size of 50, we should have 90% power to detect an effect around half the size of this estimate ($d_s = 0.65$). Based on our preregistered exclusion criteria, we excluded one participant whose accuracy was below 2 *SD* of the group mean (cutoff = 24.71%).

***One-Shot Change Localization Task***

The memory stimuli were identical to the ones used in the flicker change detection task. The main difference between the two tasks was that the two displays were presented only once in the one-shot task, and that the instructions emphasized accuracy instead of speed.

Each trial began with the presentation of a fixation cross for 500 ms. The 1$^{st}$ display was presented for 500 ms, followed by a blank delay of 900 ms. Next, the 2$^{nd}$ display was presented and remained on screen until participants clicked on the location of an item. Finally, feedback was provided by showing “CORRECT” in green or “INCORRECT” in red.

In *choice blocks*, participants were free to report either the red or blue target. However, as a control condition, in the *enforced blocks*, there was only one correct target. On *enforced-small blocks*, participants were instructed to report the target in the colour containing “fewer” items in the display; on *enforced-large blocks*, participants were instructed to report the target in the colour containing “more” items in the display.

The main task consisted of 280 trials, including 200 trials in the *choice blocks* (divided into five 40-trial blocks) and 80 trials in the *enforced blocks* (divided into four 20-trial mini-blocks). Participants first performed the *choice blocks*, followed by the strategy questionnaire used in Experiments 1 and 2. Afterwards, participants performed the *enforced blocks*, which included two *enforced-small blocks* and two *enforced-large blocks*. The order of the mini-blocks were counterbalanced across participants (ABBA, BAAB).

**Results**

Overall accuracy on the one-shot task was low ($M$ = 61.94%, $SD$ = 17.33%). There was no difference in accuracy between *choice blocks* (62.86%) and *enforced blocks* (59.64%), $t(48)$ = 1.54, $p$ = .129, 95% CI [−.97 7.40], $d_z$ = 0.22.

RTs were measured from the onset of the 2$^{nd}$ display until participants clicked on an item. For analysis of RTs, we excluded trials in which participants responded incorrectly and trials in which RTs deviated more than 2 $SD$ from the participant mean (2.36%). There was also no difference in mean correct RTs across choice blocks (1100 ms) and enforced blocks (1061 ms), $t(48)$ = 1.69, $p$ = .098, 95% CI [−7, 86], $d_z$ = 0.24.

***Enforced Block***

The optimal encoding strategy entails encoding items from the smaller subset. To verify this, we used a paired $t$-test to compare performance across *enforced-small* and *enforced-large* blocks (Figure 8a). As expected, we found higher accuracy for *enforced-small* (77.24%) compared to *enforced-large* blocks (42.04%), $t(48)$ = 14.44, $p$ < .001, 95% CI [30.3 40.1], $d_z$ =

2.06. This provides a clear demonstration that, for the *choice blocks*, selecting/encoding items from the smaller subset is more optimal than selecting/encoding items from the larger subset.

***Individual Differences***

To assess strategy use on *choice blocks*, we measured the proportion of trials participants selected an item in the small colour subset, regardless of whether participants selected the correct target (optimal colour choice). Note that we chose to use a measure of optimality that is different from what we used in flicker tasks since we predicted that accuracy would be off ceiling in the one-shot task. Alternative measures of optimality would be to compute the proportion of correct trials in which participants select the optimal target, or to compute the proportion of overall trials in which participants select the optimal target. However, these alternative measures would likely inflate or underestimate optimal strategy use.

Surprisingly, we found that strategy use was still far from optimal in the one-shot task. Mean proportion of optimal colour choice was 60.67% ($SD$ = 26.23%, ranging from 28.5% to 100%). Results were bimodally distributed (see Figure 8b), with one group of participants almost always reporting an item from the small subset, and the other group of participants reporting an item from the small subset around or less than half of the time. Further, an exploratory analysis found that optimality rate and accuracy on *choice blocks* was correlated (Figure 8c), $r$ = .88, $t(47)$ =12.80, $p$ < .001, 95% CI [.80, .93]. This confirms results from the *enforced block* analysis and shows that using the optimal strategy indeed leads to higher accuracy.

We hypothesized that participants would be more optimal in the one-shot task due to greater task demands, compared to the flicker task. However, a two-sample $t$-test did not find any difference in optimality between the current experiment (60.67%) and Experiment 1 (68.17%), $t(93) = 1.50$, $p = .137$, 95% CI [-2.42 17.4], $d_s = 0.31$.

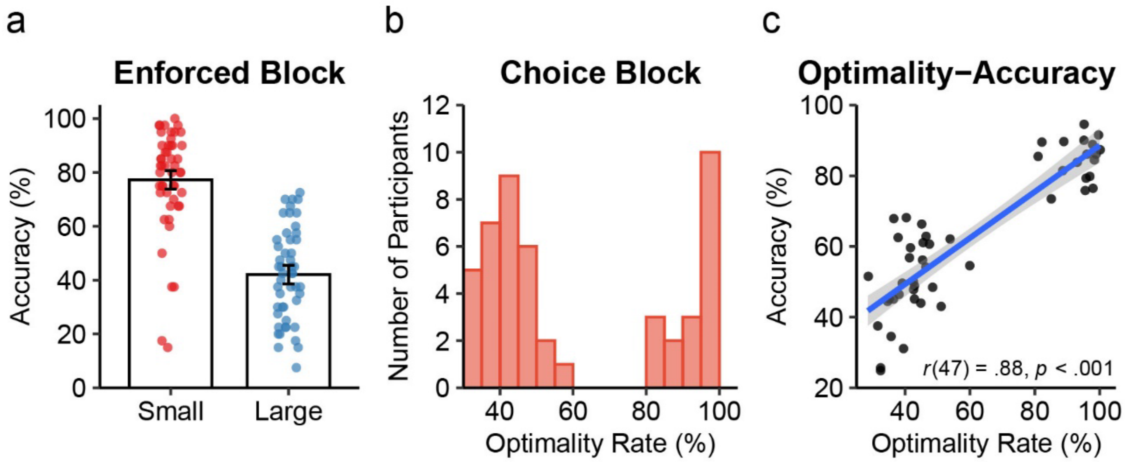


Figure 8. Strategy Optimality in the One-Shot Task. a) In the *enforced blocks*, participants were instructed to select the target in the small or large colour subset. Each dot represents a single participant, and the error bars represent within-subjects 95% confidence intervals. b) The histogram shows the distribution of optimality rate on *choice blocks*. c) The scatterplot (with best-fitting regression line) shows the relationship between optimality rate and accuracy on *choice blocks*.

**Switch rate.** Switch rate ($M = 48.81\%$, $SD = 5.54\%$) was not correlated with optimality, $r = .21$, $t(47) = 1.50$, $p = .139$, 95% CI [–.07, .47]. After excluding one univariate outlier in switch rate (25.13%, $z$ score = –4.28), there was still no correlation, $r = .19$, $t(46) = 1.31$, $p = .196$, 95% CI [–.10, .45].

**Self-reported strategy questionnaire.** Self-reported optimal strategy was correlated with higher optimality rate, $r = .83$, $t(47) = 10.29$ , $p_{\mathrm{HB}} < .001$, 95% CI [.72, .90], but not correlated with switch rate, $r = .22$, $t(47) = 1.53$, $p_{\mathrm{HB}} = .133$, 95% CI [−.07, .47]. After excluding the outlier in switch rate, we still observed no correlation, $r = .16$, $t(46) = 1.12$, $p_{\mathrm{HB}} = .269$, 95% CI [−.13, .43].

Self-reported repeated strategy was not correlated with optimality rate, $r = -.17$, $t(47) = 1.17$, $p_{\mathrm{HB}} = .247$, 95% CI [−.43, .12], but was correlated with switch rate, $r = -.56$, $t(47) = 4.65$, $p_{\mathrm{HB}} < .001$, 95% CI [−.73, −.33]. After exclusion of a univariate outlier in repeated strategy (80%, $z$ score = 4.30), we found that self-reported repeated strategy did not correlate with optimality, $r = -.13$, $t(46) = 0.90$, $p_{\mathrm{HB}} = .374$, 95% CI [−.40, .16], or switch rate, $r = -.28$, $t(46) = 1.97$, $p_{\mathrm{HB}} = .109$, 95% CI [−.52, .01].

Self-reported random strategy was not related to optimality rate, $r = -.24$, $t(47) = 1.66$, $p_{\mathrm{HB}} = .205$, 95% CI [−.48, .05]. Moreover, random strategy was not correlated with switch rate both including the outlier, $r = -.03$ , $t(47) = 0.19$, $p_{\mathrm{HB}} = .852$, 95% CI [−.31, .26], and excluding the outlier, $r = -.11$, $t(46) = 0.74$, $p_{\mathrm{HB}} = .465$, 95% CI [−.38, .18].

## Discussion

Here we examined whether individuals would adopt the optimal encoding strategy under increased task difficulty. In the one-shot task, participants can only briefly view the first display. Thus, the exact items that participants choose to encode should have a large impact on their accuracy. Most participants should be unable to identify the target accurately unless they selectively encode items in the smaller colour subset. We reasoned that the short exposure time would encourage participants to use the optimal encoding strategy. Our results showed that performance suffered greatly in the one-shot task, and that using the optimal encoding strategy indeed allowed participants to maximize task accuracy. Nonetheless, many participants still did not use the optimal encoding strategy and instead frequently reported items from the larger colour subset. This is surprising given that previous work has demonstrated that participants would use different strategies under different task requirements (Cohen-Dallal et al., 2023; Donkin et al., 2016; Fougnie et al., 2016; Udale et al., 2018; van Lamsweerde et al., 2016). Our findings suggest that greater task demands are not always sufficient to motivate more optimal strategies.

## General Discussion

What explains individual differences in WM performance? Extensive work has shown that ability accounts for substantial variation in WM performance. However, strategic factors may also contribute to WM performance. Here we used a novel approach to examine the extent to which individuals use the optimal encoding strategy in visual WM. Critically, our task allowed individuals to choose a subset of items to encode in an unconstrained manner. Moreover, we manipulated the displays such that it is more optimal for individuals to encode a specific subset of items. Experiments 1−3 used a flicker paradigm that requires participants to localize a change (target) that occur between two alternating displays. Participants are free to report one of the two available targets (one red and one blue) on each trial, and one of the target colours would contain fewer items in the display. Therefore, the optimal encoding strategy is to selectively encode items in the smaller colour subset. In all three experiments, we found that strategy use was frequently sub-optimal. Even though using the optimal encoding strategy led to better performance, individuals did not always encode items from the optimal subset. Instead, we observed large individual differences in strategy choice: Some participants almost always reported the optimal target, while others reported the optimal and non-optimal targets equally often. Given that previous work suggests a close relationship between strategy and ability (e.g., Cusack et al., 2009; Linke et al., 2011), Experiment 1 examined whether differences in WM ability determine strategy choice. Surprisingly, we found no evidence that WM capacity predicts optimal strategy use, suggesting that strategy use may be independent of ability.

Rather, our results suggest that strategy choice may reflect discovery of the optimal encoding strategy. In a two-session experiment (Experiment 2), we found that many participants initially used sub-optimal strategies and switched to the optimal encoding strategy at variable timepoints. Experiment 3 further examined the nature of this strategy change. We found that providing strategy recommendations led to a sharp rise in optimal target choice. Moreover, those who reported awareness of the optimal strategy also used this strategy more frequently. In Experiment 4, we used a one-shot variant of the task to examine whether higher task difficulty would motivate participants to adopt a more optimal encoding strategy. However, results showed that strategy use was not modulated by greater task demands.

Our findings add to existing studies examining individual differences in WM performance. While there is extensive work on individual differences in WM ability (e.g., Cowan et al., 2005; Engle, 2002; McNab & Klingberg, 2008; Unsworth et al., 2014; Vogel et al., 2005), relatively little research has examined the role of strategy use in visual WM. Some studies have explicitly instructed participants to use specific strategies (Atkinson et al., 2018; Bengson & Luck, 2016; Laine et al., 2018; Malinovitch et al., 2021; Wang et al., 2020). Similarly, others have manipulated task expectations or features of visual displays to encourage or discourage the use of certain strategies (Bor et al., 2003; Cohen-Dallal et al., 2023; Cusack et al., 2009; Fougnie et al., 2016; Linke et al., 2011; van Lamsweerde et al., 2016; Wyble et al., 2019). Although strategy use appears to have a large impact on task performance, it is unclear from these studies which strategies individuals would use by default. Moreover, many of these studies did not use a direct measure of strategy use and instead inferred that participants are using different strategies based on the performance difference across conditions. It may be more informative to use verbal self-reports to characterize the range of strategies participants use (Malinovitch et al., 2021; Nicholls & English, 2020; Ridgeway, 2006), but verbal self-reports also have some potential limitations. First, it is problematic to rely on introspection when participants may not be aware of the strategies they use (Cary & Reder, 2002). Second, it can be challenging to interpret and categorize open-ended responses. Some participants may not provide a detailed response (Fellman et al., 2020; Waris et al., 2021). Moreover, participants may report strategies they employed during encoding and/or maintenance, making it difficult to compare strategy use across individuals. Alternatively, forced-choice questionnaires may be helpful in identifying whether participants are using the strategies of interest. However, repeating these questionnaires during the experiment could potentially change participants' strategies (Waris et al., 2021). Here we relied on an alternative strategy metric, target choice, to evaluate strategy selection. By examining which targets participants report, we can infer whether participants are selecting/encoding the optimal subset. At the same time, we used strategy reports and instructional manipulation as complementary approaches to examine the role of explicit knowledge and to understand factors underlying strategy choice. Crucially, self-reported strategy use from both verbal reports and forced-choice questionnaires is largely consistent with target choice behaviour, thus providing converging evidence that individuals vary in strategy choice.

The current study focused on selective encoding strategies since attentional selection during encoding has important consequences for WM performance (Fukuda et al., 2015; McNab & Klingberg, 2008; Robison et al., 2018; Vogel et al., 2005). Indeed, many participants reported using a strategy of focusing on one colour or one part of the display. However, individuals may also simultaneously use other strategies, such as remembering several items as a shape. Future work is necessary to examine the range of strategies individuals use during encoding, maintenance, and/or retrieval.

Crucially, our results provide new evidence for the role of explicit knowledge in strategy use. The benefit of strategy instructions shown in Experiment 3 is consistent with work on WM strategy training. Previous studies showed that training participants to use specific strategies leads to large improvements on trained tasks (Laine et al., 2018; Malinovitch et al., 2021; Turley-Ames & Whitfield, 2003). A few studies also found transfer to untrained yet similar tasks in which the same strategies can be implemented (Fellman et al., 2020; Gathercole et al., 2019; Laine et al., 2018; Linares et al., 2019; McNamara & Scott, 2001; see also Dunning & Holmes, 2014). According to these studies, acquisition of new strategies may explain why WM training improves performance (cf. Himi et al., 2022). Thus far, only a few studies have explored the extent to which individuals develop effective WM strategies, largely in n-back tasks, in the absence of explicit instructions (Fellman et al., 2020; Laine et al., 2018; Malinovitch et al., 2021; Waris et al., 2021). Even after weeks of uninstructed practice, only some of the participants used the optimal strategy (Fellman et al., 2020; Malinovitch et al., 2021). More importantly, similar to our study, there is variability in when individuals start using the optimal strategy in n-back tasks (Malinovitch et al., 2021). It will be informative for future research to use modeling approaches to analyze learning curves at the individual level (e.g., Musfeld et al., 2022; Wynton & Anglim, 2017).

It is worth noting that research in other cognitive domains has reported similar findings of strategy change. For example, several studies have asked participants to perform a perceptual decision task based on the location of a dot array (Allegra et al., 2020; Gaschler et al., 2019; Schuck et al., 2015, 2022). Unknown to the participants, the colour of the dot array is related to its location. Thus, participants could have relied on the colour instead of the location to perform this task. Only some participants ended up using this alternative, colour-based strategy, and they varied in when they started using this strategy. It remains an open question whether individual differences in learning rate may reflect a unique cognitive trait. For example, individuals who discover the alternative strategy in one task may be more likely to use the shortcut in another task. There could be differences in how quickly individuals extract regularities from the environment (e.g., Rose et al., 2010; Schuck et al., 2015), or how quickly individuals update knowledge about strategy effectiveness (Hertzog et al., 2008; Schunn et al., 2001; see also Domenech et al., 2020; Donoso et al., 2014). Future work may further explore whether spontaneous discovery of the optimal strategy relates to insight problem solving (Kounios & Beeman, 2014) and the sudden onset of Hebb repetition learning (Musfeld et al., 2022; Souza & Oberauer, 2022).

Although our results highlight the importance of strategy discovery, we do not imply that explicit knowledge is the only factor that determines strategy use in WM. Studies from our lab have used the Adaptive Choice Visual Search task, whose design the current study was based on, to investigate factors underlying strategy choice (Irons & Leber, 2016, 2018). At first glance, there are some similarities between our findings and those from visual search studies. There are large individual differences in strategy use, with many participants using sub-optimal strategies frequently. However, one important difference is that the lack of explicit knowledge only partly explains why individuals use sub-optimal strategies in visual search. The current study showed that providing strategy recommendations induced a large strategy change in visual WM, whereas the same manipulation only led to a modest 10% improvement in visual search optimality (Zhang et al., in prep). Instead, avoidance of cognitive effort may play an important role in visual search strategies. Individuals who rated the optimal visual search strategy as less effortful and more effective were more likely to use this strategy (Irons & Leber, 2018). Although we did not directly assess cognitive effort in the present study, the majority of participants followed optimal strategy recommendations or complied with instructions in the enforced blocks. Therefore, we believe that subjective effort only plays little role in strategy choice in visual WM.

The present work has implications for the psychometric properties of WM paradigms. Many studies were concerned about the reliability of WM measures in estimating individual differences (M. Dai et al., 2019; Pailian et al., 2020; Pailian & Halberda, 2015; Xu et al., 2018; Zhao et al., 2022). However, it may be equally important to ask to what extent these WM measures reflect differences in ability, differences in encoding strategy (Atkinson et al., 2018; Bengson & Luck, 2016; Wang et al., 2020), and/or differences in response strategies (KyllingsbæK & Bundesen, 2009; Williams et al., 2022). Critically, it is not always straightforward to quantify the contribution of strategy and ability to WM performance. Future studies, including those manipulating strategy instructions and/or using brain stimulation techniques (e.g., Assecondi et al., 2021; Jones et al., 2015; Wang et al., 2020), will be helpful in elucidating the role of strategy and ability in WM.

The present study demonstrates large individual differences in encoding strategy in visual WM. Although some individuals adopt the optimal encoding strategy, many others use sub-optimal strategies frequently. Our results highlight an important way in which strategy and ability might produce distinct contributions to individual differences. Further, we provided evidence that explicit knowledge plays a key role in strategy choice. Moreover, we found that strategy use was not modulated by greater task demands. Together, our results emphasize the importance of investigating strategy use to better understand visual WM performance.

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