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Fluid intelligence correlates with working memory capacity for both real-world objects and simple-feature stimuli☆

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ABSTRACT

Previous research has shown that individual differences in visual working memory performance strongly correlate with measures of fluid intelligence. In these studies, visual working memory was assessed using simple feature stimuli, such as oriented lines or colored squares, as traditionally done. However, recent studies have shown that working memory performance is higher for meaningful stimuli (i.e., real-world objects) relative to simple features. How does working memory capacity for real-world objects relate to fluid intelligence? To test this, participants (103 young adults) completed different visual working memory tasks that used images of real-world objects or simple colored circles as well as fluid and crystallized intelligence tests. The results showed reliable correlations between all working memory tasks and fluid intelligence scores, and no significant differences between these correlations across stimulus types. Interestingly, fluid intelligence scores were correlated with the difference in working memory performance between real-world objects and colored circles, suggesting that the increase in working memory capacity for meaningful stimuli relates to fluid intelligence abilities. Working memory performance was not reliably correlated with crystallized intelligence in any of the tasks. Collectively, these findings suggest that maintaining real-world objects and colored circles largely rely on shared cognitive processes that may, in part, underlie individual differences in fluid intelligence.

Introduction

Working memory refers to the cognitive function of maintaining task-relevant information in a readily accessible state and manipulating it according to current task demands (Baddeley, 1992). Its capacity is highly limited and varies between people in important ways. For example, deficiencies in working memory functioning have been associated with various disorders such as learning disabilities (Swanson & Siegel, 2011), attention-deficit/hyperactivity disorder (Kasper et al., 2012), and schizophrenia (Park & Holzman, 1992). Interestingly, individual differences in working memory performance – more specifically, *visual* working memory performance – have also been shown to correlate with measures of *fluid intelligence,* the ability to reason, solve novel problems, and adapt to new environments (Cattell, 1963; Horn, 1968; Conway et al., 2002). Fluid intelligence is related to, but separable from, *crystallized intelligence*, which reflects learned abilities, such as vocabulary or general knowledge. Fluid and crystallized intelligence are usually measured with a battery of diverse cognitive tests including tasks of processing speed, attentional control, problem solving, and vocabulary knowledge. The measure of *general intelligence* (– the factor *g* –) emerges from the positive correlation among these tests, and is traditionally thought of as reflecting a domain-general, core cognitive ability underlying all of these tasks (Spearman, 1904; Jensen, 1998; Kovacs & Conway, 2019; van der Maas et al., 2006) that can predict academic achievement (Rohde & Thompson, 2007) and career success (Schmidt & Hunter, 1998).

While a wealth of previous studies has demonstrated a strong relationship between visual working memory and fluid intelligence, many of them have relied on simple, abstract stimuli to assess working memory capacity, which may not fully reflect how visual working memory operates in more ecologically valid contexts where we remember not just abstract shapes, but meaningful objects that we can interact with and have knowledge about. Thus, in this study, we investigate whether individual differences in visual working memory for such meaningful objects also correlate with fluid intelligence levels. This is an important question because fluid intelligence is often linked to (and measured as) abstract visual reasoning that does not interact with semantic knowledge. Thus, it is unclear whether this abstract reasoning system

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underlying fluid intelligence would predict performance in a visual working memory task that relies, at least in part, on prior conceptual and semantic knowledge.

The relationship between visual working memory and fluid intelligence

To investigate the relationship between working memory and fluid intelligence, researchers have often used various span tasks that not only require participants to maintain information for short periods of time, but also to manipulate and process information in complex ways. For example, participants are asked to remember a set of alphabet letters while at the same time engaging in secondary tasks such as arithmetic calculations (e.g., Unsworth & Engle, 2005; Conway et al., 2002; Engle et al., 1999). Other studies have shown that fluid intelligence is also correlated with performances in visual working memory tasks where participants are asked to solely *maintain* visual information for a short period of time, without additional complex manipulations (e.g., Fukuda et al., 2010; Unsworth et al., 2014). This has led researchers to propose that the mere capacity to store abstract visual information for short periods of time also correlates with fluid intelligence. The function of visual working memory is often described as maintaining visual continuity across eye movements in a visual scene, where perceptual disruptions – due to the saccade – require the visual system to perpetuate inputs from one eye movement to the next (e.g., Cronin & Irwin, 2018; Hollingworth et al., 2008). Thus, visual working memory is thought to be deeply related to the eye movement system (van der Stigchel & Hollingworth, 2018) and to be intricately connected to lower-level perceptual processes (Scimeca et al., 2018; Adam et al., 2022). It is traditionally studied using change-detection tasks, where participants are asked to maintain an array of visual items over a short delay period to then indicate which items they just saw in a test display (e.g., Luck & Vogel, 1997). Using this task, several studies have found strong correlations between performance on these relatively simple and low-level visual working memory tasks and abstract reasoning skills, such as the Raven's matrices test, a standard measure of fluid intelligence (e.g., Cowan et al., 2005; Unsworth et al., 2014; Fukuda et al., 2010; Unsworth et al., 2015). While the exact nature of this relationship is still under investigation, studies have suggested that working memory capacity may serve as an explanatory construct for abstract reasoning that can account for a significant portion of variance in individuals' intelligence abilities (e.g., Oberauer et al., 2005; Kyllonen & Christal, 1990), with some studies demonstrating a causal relationship between the two (e.g., Hagemann et al., 2023).

Critical for the present work, to date, previous studies have mostly used simple and abstract stimuli when measuring visual working memory, such as colored squares or oriented lines. Thus, it is unknown whether these correlations depend – at least to some extent – on the visual materials being abstract, just like in the Raven's matrices test, or whether maintaining concrete and semantically meaningful stimuli in working memory would also relate to fluid intelligence measures. This is an important and timely question given the recently emerging evidence that visual working memory capacity differs depending on what type of information people are remembering and is increased for meaningful and familiar objects (for a recent review, see Chung, Brady & Störmer, 2024).

Visual working memory capacity for real-world objects and simple features

The vast majority of studies examining visual working memory processes have conventionally used simple and/or abstract stimuli (e.g., Cowan et al., 2005; Fukuda et al., 2010; Unsworth et al., 2014; Unsworth et al., 2015; Duncan et al., 2012), mainly because the usage of abstract stimuli can help isolate visual working memory from other cognitive processes like chunking or passive forms of memory (Cowan, 2001). However, in many ways, tasks using simple features or arbitrary shapes are highly abstracted versions of how we interact with visual information in the real world, where we see and memorize meaningful objects: cups, tables, and people – stimuli that are not only much more visually complex but also more meaningful and familiar to us. This discrepancy creates a disconnect between how visual working memory capacity is often measured in lab settings and the ways in which we use this system in everyday vision. In fact, it has been suggested that using simple artificial shapes might have resulted in chronically underestimating individuals' working memory capacity (Brady et al., 2016; Brady & Störmer, 2022), as using simple and abstract stimuli overlooks our visual system's ability to rapidly process and store conceptually rich information (Potter, 1993). Consistent with this, recent studies found that when participants are asked to maintain images of real-world objects over short periods of time, working memory performance is higher relative to when maintaining simple low-level features, despite these objects being visually more complex (e.g., Brady et al., 2016; Brady & Störmer, 2022; Brady & Störmer, 2023; Thibeault et al., 2024; Torres et al., 2024; for a review see Chung et al., 2024). The critical factor underlying this working memory benefit appears to be that real-world objects connect to pre-existing knowledge, as other work has shown that increasing the visual complexity of objects alone actually results in lower visual working memory performance (e.g., polygons or letters of an unfamiliar language; Alvarez & Cavanagh, 2004; Luria et al., 2010). Indeed, stimuli that are recognized as meaningful result in better memory performance than stimuli that are not recognized as meaningful even when these stimuli are roughly matched visually (Brady & Störmer, 2022). One study by Asp et al. (2021) showed that ambiguous stimuli (Mooney images) were better remembered when they were recognized as a human face compared to when they were only perceived as random visual patterns, despite being physically identical. Thus, meaningful stimuli recruit additional visual working memory capacity, presumably because they allow the extraction and maintenance of more relevant visual and semantic features (i.e., once the image is recognized as a face, detailed visual features are meaningful as they can be interpreted in terms of age, gender, and emotion, and not just abstract black and white patterns).

Overall, these findings suggest that our ability to actively maintain visual information is strongly dependent on the type of information that is being remembered, and that establishing links between the to-be-remembered objects and pre-existing conceptual knowledge may play an important role in visual working memory processes. However, how such perceptual-conceptual links in visual working memory relate to measures of fluid intelligence that are usually assessed with highly abstract visual reasoning tasks, remains an open question.

The current study

Based on the recent evidence showing that meaningful stimuli, such as real-world objects, are better maintained in visual working memory than simple and meaningless shapes, we here ask: Does the previously observed relationship between visual working memory capacity and fluid intelligence extend to working memory tasks that use more complex and meaningful real-world objects? On the one hand, it could be that visual working memory tasks that use meaningful and abstract stimuli share processes that relate to measures of fluid intelligence, in which case a correlation should be present regardless of stimulus type. On the other hand, given that visual working memory capacity for real-world objects is tied to conceptual knowledge and semantic meaning (Asp et al., 2021; Brady et al., 2024; Chung et al., 2024; Wyble et al., 2016), it is plausible that no clear relation emerges with measures of fluid intelligence, which are thought to assess abstract visual reasoning skills in particular – an aspect that is considered to be aligned with the abstract nature of previous working memory tasks (e.g., Oberauer et al., 2005). Therefore, it remains unclear whether performance in tasks using real-world objects would tap into the same limits impacting the relationship between working memory tasks using simple stimuli and fluid intelligence tests.

We here examined how visual working memory performances in tasks using real-world objects relate to fluid intelligence scores assessed via the Raven's Advanced Matrices test (Raven et al., 1993), a well-validated and highly reliable metric for measuring people's fluid intelligence level (Raven, 2000). We hypothesized that if visual working memory tasks with real-world objects strongly rely on passive long-term storage that is governed by prior knowledge, it may reduce or replace some of the abstract working memory processes used for simple features, and thereby not correlate robustly with fluid intelligence scores. In contrast, if involvement of conceptual knowledge does not reduce active working memory processes related to fluid intelligence, individuals' working memory performances with complex and meaningful stimuli should correlate reliably with fluid intelligence scores. In addition, we examined how visual working memory performances correlate with measures of crystallized intelligence using scores from the C-Test, a test that has been found to reliably capture language proficiency, one important aspect of crystallized intelligence (Grothjahn et al., 2002; Eckes & Grotjahn, 2006; Harsch & Hartig, 2016). We added the C-Test to explore the possibility that working memory performance for real-world objects is related to aspects of semantic or verbal knowledge, based on the fact that these objects interact with pre-existing conceptual knowledge. However, given that the memory task itself remains to be of visual nature primarily, even if the meaningful and recognizable stimuli connect to prior knowledge, we did not necessarily expect a strong relation between real-world object working memory and the language-based crystallized intelligence test. We did predict that working memory performance for both colored circles and real-world objects would correlate reliably with fluid intelligence scores, and that both tasks would strongly correlate with one another. Our results were consistent with these predictions, suggesting that visual working memory performances for different types of stimuli share underlying processes related to fluid intelligence.

Methods

The hypothesis, analysis plan, sample size, and exclusion criteria for this study were pre-registered (https://osf.io/8bj6k). All data are available online (https://osf.io/djg2b/). Statistical analyses were performed in R (version 4.0.2) and R Studio (version 1.3.1093).

Participants

111 undergraduate students from Dartmouth College were recruited to participate in the study in exchange for 1 class credit/hr. Data from six participants were excluded due to prior exposure to either form of intelligence test. Data from one participant were excluded due to a laptop malfunction during the test session, and data from one additional participant were excluded due to failure to properly follow test instructions. No participant was excluded due to their overall d' of visual working memory tasks being lower than zero (chance level) or more than 20 % of their trials being rejected (both *a priori* exclusion criteria described in the pre-registration). Individual trials were excluded if response times were shorter than 200 ms or longer than 5,000 ms. In total, data from 103 participants were used in the main correlation analysis between working memory tests and fluid intelligence (Mean Age = 19.34, Age Range = [18–24], 69 Female, 34 Male; see Supplementary Materials for more detail). For the C-Test data analysis, data from 13 participants were excluded due to not having English as their first language, and data from another 4 participants were excluded due to not following the task instructions, resulting in 86 participants for this analysis. Although the pre-registration specified 100 participants for the main analysis, we intentionally overshot the number of participants in recruitment to account for potential exclusions. The number of participants was guided by the precedent set in similar previous investigations of fluid intelligence and visual working memory that while variable, hovered around a similar number on average (e.g., 100 participants in Babic et al., 2019; 79 participants in Fukuda et al., 2010; 171 participants in Unsworth et al., 2014; 65 and 113 participants in Schubert et al., 2023). Post-hoc power analyses based on the effect sizes reported in the above-mentioned studies suggest that roughly 60–70 participants would be needed to achieve a power of 0.80 for finding a reliable correlation between visual working memory measures and fluid intelligence. Thus, as the main goal of our study was to see *whether* visual working memory for real-world objects correlates with fluid intelligence scores, and not whether that correlation would differ for real-world objects vs. simple features, we deemed 100 participants to be appropriate. We decided to use a slightly larger sample than the one suggested by the power analysis given that these previous reports are based on working memory tasks with simple stimuli and not real-world objects. All experimental procedures were approved by the Committee for the Protection of Human Subjects at Dartmouth College.

Stimuli and procedure.

This study was a within-subjects design where each participant was exposed to all conditions. There were a total of 2 intelligence tests (Raven's Advanced Progressive Matrices and C-Test) and 3 working memory tests, with the latter tests split into two parts: part 1 included two conditions, the sequential visual working memory task for colored circles and the sequential visual working memory task for real-world objects; part 2 included the simultaneous visual working memory task for colored circles with spatial locations (see below for more details). The sequence of the fluid intelligence test, crystallized intelligence test, and working memory tests was randomized per each study session. For the sequential working memory tests, the block order of color visual working memory task and object visual working memory task was counterbalanced and was then always followed by the simultaneous color visual working memory task with spatial locations (see below).

Each study session consisted of 1 to 9 participants at once (on average about 5) in a designated study room. Participants completed the intelligence tests on printed copies and the working memory tasks on their individual laptops. During the study session, participants were not allowed to converse or exchange answers in the testing room. Two standardized 5-minute breaks were given between each test. Prior to the study session, participants were asked to complete an online color blindness test (colormax.org) and score over 10 out of 12 in order to participate in the study. Any participant who did not score over 10 was unable to participate. Upon arrival, participants completed a demographics survey which asked for their age, academic year, gender, current GPA, college entrance exam scores, and English language proficiency (see Supplementary Materials for details). Participants also performed a selective ensemble perception task (Ortego & Störmer, 2024) as described in the pre-registration, to explore a potential relationship between a novel selective feature attention task developed by our lab and fluid intelligence. This data is reported in the Supplementary Materials.

Sequential object & color visual working memory task

The object and color visual working memory task followed the same general structure. On each trial, participants were presented with either 4 real-world objects or 4 colored circles. Stimuli (150 px in width and 150 px in height) were presented one at a time at the central location of the screen for 200 ms each, with a 200 ms inter-stimulus-interval. We adopted a sequential presentation of the stimuli to maximize performance differences between these tasks, following recent studies showing a larger real-world object benefit for sequential relative to simultaneous stimulus presentation, possibly due to deeper processing of each stimulus (Brady & Störmer, 2022; Chung et al., 2023a). After an 800-ms delay, participants were presented with a two-alternative-forcedchoice (2-AFC) test in the center of the screen with two different stimulus choices: one matching one of the stimuli at encoding (target) and one that was a novel foil. We used a 2-AFC task as usually done in our lab, based on findings indicating that performance on this task correlates well with other working memory performance measures (Schurgin et al., 2020) and because it minimizes response biases as well as perceptual confusions at test (Williams et al., 2022; Brady et al., 2023). Object stimuli were selected from 540 images of real-world objects from Brady et al. (2008). Object foils were chosen from the database to be maximally dissimilar from the target object determined by convolutional neural networks (Brady & Störmer, 2023). This ensured that participants could discriminate the target and foil stimulus similarly well across the different stimulus sets, so that differences in memory performance across stimulus types would not be due to differences in perceptual discriminability between the targets and foils (for a longer discussion on this, see Brady & Störmer, 2023). For the color memory condition, colors were chosen from a CIE L*a*b* color wheel similar to prior works (e.g., Suchow et al., 2013; Schurgin et al., 2020) and were randomly selected on each trial with the constraint that the to-be-remembered colors were at least 30 degrees apart from each other. Concuring the selection of the maximally dissimilar foil in the object condition, the foil color was also selected to be maximally dissimilar – 180 degrees away on the color wheel – from the target color and at least 30 degrees away from the other to-be-remembered colors. Participants indicated which one of the two options they had previously seen by pressing the left or right arrow key. After each report participants were given visual feedback on their answer. Each condition comprised 60 trials, for a total of 120 trials per participant, distributed across four blocks of 30 trials each. Block order was counterbalanced across participants. Prior to the experiment, participants were given a short instructional video demonstrating the task. See Fig. 1A and 1B for an illustration of the task design.

Simultaneous color visual working memory task with spatial locations

Previous research investigating correlations between simple feature working memory (i.e., colored squares) performance and fluid intelligence scores has frequently used simultaneous presentation during memory encoding where all memory items are presented at once (e.g., Babic et al., 2019; Fukuda et al., 2010; but see Schubert et al., 2023 for sequential spatial working memory). To allow for more direct comparisons with this previous work and the sequential design described above, we included an additional visual working memory task using simultaneous presentation. The procedure was identical to the task above with the following exceptions: on each trial 4 colored circles were simultaneously presented at locations evenly distributed around the center of the screen for 800 ms. After a 800-ms delay, participants were presented with a spatial cue indicating the location of the target item along with a 2-AFC with the target color and a foil color. Participants were instructed to report which of the two colors they previously saw at the bolded location by clicking the corresponding response probe. Colors were chosen as in the sequential presentation described above. There were 60 trials in total. Prior to the experiment, participants were given a short instructional video demonstrating the task. See Fig. 1C for illustration of the task design.

Fluid intelligence test: raven's advanced progressive matrices

Fluid intelligence was measured using the Raven's Advanced Progressive Matrices (Raven et al., 1993), consistent with previous works investigating the relationship between fluid intelligence and working memory for color (e.g., Fukuda et al., 2010; Babic et al., 2019; Unsworth et al., 2014; Unsworth et al., 2015; Schubert et al., 2023). The Raven's test involves abstract reasoning and problem solving, consisting of 36 problems that get increasingly difficult. Each problem features a three-

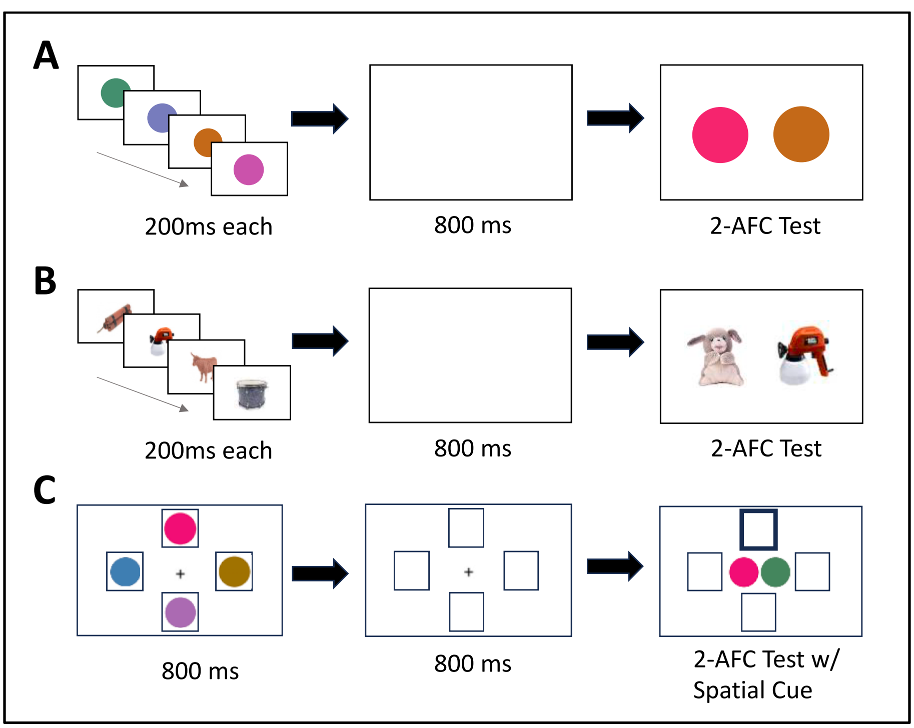

Fig. 1. Procedures for the visual working memory tasks. **A)** Sequential Color Working Memory Task: Four colored circles were presented sequentially (one item at a time) in the center of the screen, followed by a short delay and a 2-AFC test in the center of the screen in which participants had to indicate which of two colors they saw during encoding. **B)** Sequential Object Working Memory Task: The same procedure was repeated with real-world objects. **C)** Simultaneous Color Working Memory Task with Spatial Locations: Four colored circles were presented simultaneously at four distinct locations on the screen, followed by a short delay and a 2-AFC test with a spatial cue indicating the target location. Participants had to report which color they saw at the cued location. All image sizes are not to scale and are for illustration purposes only.

by-three matrix of geometric patterns with a missing piece. The task was to determine the logical continuation for each set of three-by-three matrices. Participants were instructed to complete as many problems as possible within a 30-minute time frame, starting with a five-minute practice test to familiarize themselves with the task format. See Fig. 2A for an example problem from the practice test.

Crystallized intelligence test: C-test

The C-Test is a test of general language proficiency. We used a version of the C-Test from Keijzer (2007). Participants were given 5 texts containing 20 word gaps where parts of the sentences had been omitted. The task was to fill in the gaps with the correct word with the correct lexical stem. The total duration of the test was 10 min. Prior to the main test, participants completed a 2-minute practice C-Test. See Fig. 2B for the practice C-Test.

Analysis

Sequential object & color working memory tasks

To assess performance on the sequential visual working memory tasks, d' values were calculated separately for the 2 conditions for each participant (objects vs. colors) as a measure of memory strength: (z[hits] – z[false alarms])/$\sqrt{2}$. Due to the calculation of d', perfect hit rates in any condition were adjusted by applying $(n – 0.5)/n$ where n is the number of trials (Macmillan & Kaplan, 1985). The hit rates of four participants were adjusted accordingly in the object working memory task. These d' values were then compared using a pairwise t-test. To measure the reliability of the task performance, we used the Spearman-Brown reliability test, which involved splitting the data into even and odd trials, calculating the correlation between these splits, and applying the Spearman-Brown formula to estimate the reliability coefficient.

Simultaneous color working memory task with spatial locations

To assess performance on the simultaneous visual working memory task with spatial locations, d' values for a 2AFC task were calculated for each participant (see above). These values were then compared with sequentially presented color and object working memory performances using pairwise t-tests. The Spearman-Brown reliability test was used to assess the reliability of the task performance.

Fluid intelligence test

Participants' test scores were calculated by tallying the number of correct responses out of a total of 36.

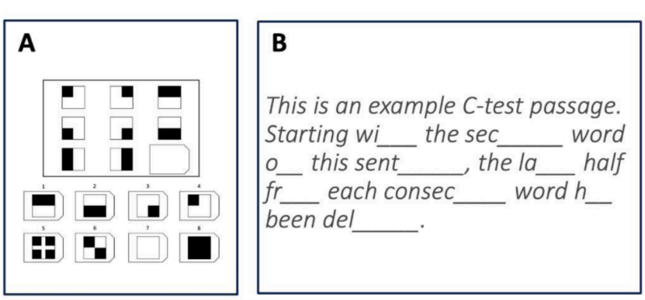

Fig. 2. Practice examples of the Raven's Advanced Progressive Matrices Test (A) and C-Test (B). A) Participants determined the logical continuation of the 3X3 matrix by indicating the correct number (1–8). The example Raven's test is from the practice Raven's test. B) Participants filled in the gaps with the correct word. The C-Test example is from Norris (2018).

Crystallized intelligence test

Participants' test scores were calculated by tallying the number of correct responses out of a total of 100. Scores were coded following these guidelines: Correct words, acceptable variants, and words with simple spelling errors were coded as correct, while incorrect words, words with grammatical errors, and blank responses were coded as incorrect.

Correlation analysis

Correlations among various cognitive and intelligence test performances were tested by computing Pearson's correlation coefficients. We then tested significant differences between correlations using Fischer r-to-z transformation. Although our pre-registration included estimating the reliability of each measure using the Spearman-Brown correction, this was not easily available for intelligence test scores as each test question gets progressively harder, making it challenging to perform split-half analysis.

Results

Sequential object & color working memory tasks

We first compared the visual working memory performances between the sequential object working memory task and sequential color working memory task. We found that participants performed significantly better in the real-world object working memory task (mean d' = 2.10, standard deviation = 0.55) compared to the color working memory task (d' = 1.28, standard deviation = 0.31; $t(102) = 16.85$, $p < 0.001$, Cohen's $d_z = 1.72$; see Fig. 3), replicating previous results (Brady et al., 2016; Brady & Störmer, 2022; Brady & Störmer, 2023; Thibeault et al., 2024; Torres et al., 2024). This effect was already robustly found in the first few trials of the experiment, demonstrating that the difference in performances was not driven by a buildup of long-term interference due to stimulus repetition (see Supplementary Materials). The Spearman-Brown split-half reliability analysis yielded a coefficient of 0.62 for the sequential object working memory task and 0.29 for the sequential color working memory task, indicating that using real-world objects resulted in relatively higher reliability than using colored circles when sequentially presented.

Simultaneous color working memory task with spatial locations

Mean d' for the simultaneous color working memory task with spatial locations and a spatial cue at response was 1.15 with a standard deviation of 0.59. We found that performance from the simultaneous-presentation color visual working memory task with spatial locations was significantly lower compared to the sequentially presented object working memory task ($t(102) = 15.29$, $p < 0.001$, Cohen's $d_z = 1.66$) and sequential color working memory task ($t(102) = 2.51$, $p = 0.01$, Cohen's $d_z = 0.27$). The Spearman-Brown reliability analysis yielded a coefficient of 0.79 (see Fig. 3).

Fluid intelligence and crystallized intelligence task

Overall, participants performed well in the Raven's Advanced Progressive Matrices test with a mean score of 24.99 and standard deviation of 5.04. For the C-Test, the mean score was 70.16 and the standard deviation was 11.53. Note that we only included C-Test scores from participants who reported English as their first language.

Visual working memory performances correlate with fluid intelligence scores

We found that sequential visual working memory performances for both real-world objects and colored circles significantly correlated with

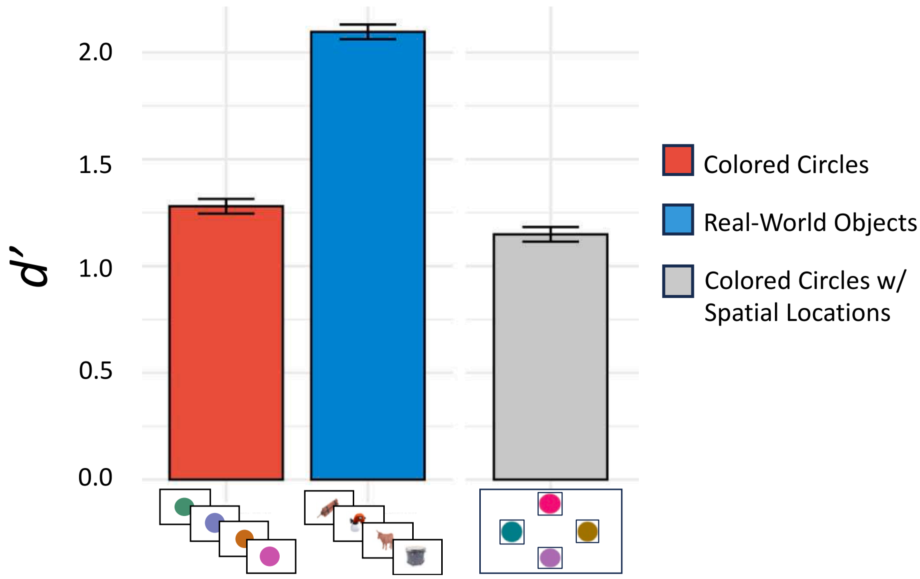

Fig. 3. Results of the sequential visual working memory tasks for colored circles (red) vs. real-world objects (blue) along with the simultaneous color visual working memory task with spatial locations (grey). Real-world objects resulted in better working memory performance than colored circles, replicating previous studies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Raven's task scores (real-world objects: $r(101) = 0.38$, $p < 0.001$; colored circles: $r(101) = 0.25$, $p = 0.01$; see Fig. 4A). While the correlation coefficient between working memory for real-world objects and fluid intelligence scores was numerically higher than the correlation between working memory for colors and fluid intelligence scores, a comparison using Fisher's R-to-Z transformation resulted in no significant difference between the two correlations ($Z = 1.34$, p(two-tailed) $= 0.18$). Simultaneous color working memory with spatial locations also significantly correlated with Raven's task score ($r(101) = 0.29$, $p = 0.003$; see Fig. 5D).

We also examined whether the increase in working memory performance for real-world objects relative to colors would correlate with fluid intelligence scores. To do so, we computed the d' difference between the sequential object and color memory tasks and correlated this difference with the intelligence scores. Interestingly, we observed a significant positive correlation ($r(101) = 0.26$, $p = 0.007$). Thus, individuals who showed a stronger object benefit also tended to have higher fluid intelligence test scores. No such correlation was found with C-Test scores ($r(101) = 0.01$, $p = 0.89$).

The C-Test score did not significantly correlate with sequential working memory performance for either real-world objects ($r(84) = 0.08$, $p = 0.44$) or colored circles ($r(84) = 0.17$, $p = 0.12$; see Fig. 4B). Comparison using Fischer R-to-Z transformation resulted in no significant difference between the two correlations ($Z = 0.79$, p(two-tailed) $= 0.42$). There was also no correlation between simultaneous color working memory with spatial locations and the C-Test ($r(84) = 0.05$, $p = 0.63$; see Fig. 5E).

As expected, all three visual working memory measures were significantly correlated with each other (sequential real-world objects vs. sequential colored circles: $r(101) = 0.46$, $p < 0.001$; sequential real-world objects vs. simultaneous colored circles with spatial locations: $r(101) = 0.39$, $p < 0.001$; sequential colored circles vs. simultaneous colored circles with spatial locations: $r(101) = 0.40$, $p < 0.001$; see Fig. 5A-C). We also found that Raven's task scores significantly correlated with C-Test scores ($r(84) = 0.26$, $p = 0.02$; see Fig. 5F). See Table 1 for a summary of all correlation results and Table 2 for summary statistics of measures from all tasks.

Discussion

Recent findings have shown that visual working memory performance is reliably increased for meaningful real-world objects compared to simple abstract shapes and features (Brady et al., 2016; Brady & Störmer, 2022; Thibeault et al., 2024; Torres et al., 2024). Here we

Fig. 4. Relationship between sequential visual working memory tasks for objects and colors and the intelligence tests. Each dot represents one subject. **A)** Reliable correlations were observed between individual scores on the Raven's task and performances (d') in both the sequential real-world object (blue) and color (red) working memory tasks. **B)** No reliable correlations were observed between individual scores in the C-Test and performances (d') in the sequential real-world object (blue) and color (red) working memory tasks. Histogram plots illustrate the distribution of scores for both the x and y variables in each graph, representing the score distributions of the respective tasks. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

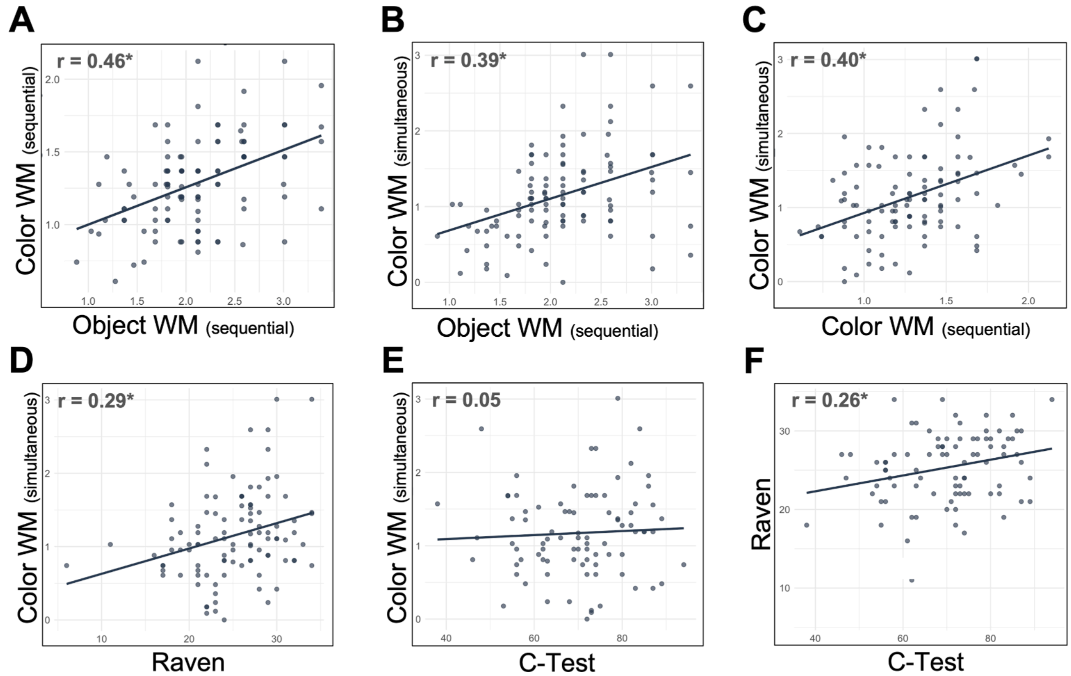

Fig. 5. Correlation plots across all other tasks. **A)** Sequential object working memory vs. sequential color working memory tasks. **B)** Sequential object working memory vs. simultaneous color working memory task with spatial locations. **C)** Sequential color working memory vs. simultaneous color working memory with spatial locations. **D)** Raven test vs. simultaneous color working memory task with spatial locations. **E)** C-Test vs. simultaneous color working memory with spatial locations. **F)** C-Test vs. Raven test. All tasks showed significant correlations except between the working memory tasks and the C-Test.

Table 1
Summary of correlation analysis results. Values indicate correlation coefficients and asterisks indicate significance.

	WM Objects (Sequential)	**WM Colors (Sequential)**	**WM Colors (Simultaneous)**	**Raven's Test**	**C-Test**
WM Objects (Sequential)	X				
WM Colors (Sequential)	**0.46***	X			
WM Colors (Simultaneous)	**0.39***	**0.40***	X		
Raven's Test	**0.38***	**0.25***	**0.29***	X	
C-Test	0.08	0.17	0.05	**0.26***	X

Table 2
Summary statistics of measures from all tasks.

	Mean	**SD**	**Range**	**Skewness**	**Kurtosis**	**Reliability**
Object WM (Sequential)	2.09	0.55	0.88–3.39	0.32	2.89	0.62
Color WM (Sequential)	1.28	0.31	0.61–2.12	0.29	2.94	0.29
Color WM (Simultaneous)	1.15	0.59	0–3.01	0.77	4.01	0.79

	Mean	**SD**	**Range**	**Skewness**	**Kurtosis**
Raven's Test	24.99	5.04	6–34	−0.64	3.99
C-Test	70.16	11.53	38–94	−0.32	2.61

examined how such improved visual working memory performance is related to fluid intelligence, the ability of abstract reasoning, which is well known to be correlated with visual working memory performance for simple and abstract stimuli. We hypothesized that if visual working memory for real-world objects and colored circles share underlying processes that are related to fluid intelligence, then performances on both tasks should reliably correlate with fluid intelligence scores. Conversely, if visual working memory performance for meaningful stimuli relies on different processes, for example those that are related to long-term semantic and verbal knowledge, then it may not correlate robustly with fluid intelligence and potentially be related to measures of crystallized intelligence instead. Our results show that individual differences in visual working memory performances for both objects and simple stimuli are reliably correlated with measures of fluid intelligence, but not crystallized intelligence, regardless of stimulus type. Our findings validate the previously established relationship between visual working memory and fluid intelligence, and extend it to also encompass more complex and meaningful stimuli. Overall, these findings suggest that core active memory processes that are related to fluid intelligence are similarly involved when maintaining simple features and real-world objects in visual working memory.

Visual working memory performance is correlated with fluid intelligence level

Visual working memory has traditionally been studied using abstract and simple stimuli, based on the premise that working memory operates independently of semantic knowledge or conceptual structures (Oberauer et al., 2005). Likewise, fluid intelligence comprises cognitive abilities where no prior semantic knowledge is useful, such as abstract figural reasoning, rather than concrete figural reasoning (Schulze et al., 2005) or language (Woolgar et al., 2018). Consequently, many studies investigating the relationship between visual working memory and fluid intelligence have used abstract stimuli for working memory tasks including arrays of colored circles (e.g., Fukuda et al., 2010; Unsworth et al., 2015; Duncan et al., 2012), oriented lines (e.g., Unsworth et al., 2015; Unsworth et al., 2014), random dot patterns (e.g., Schubert et al., 2023; Dang et al., 2012; Haavisto & Lehto, 2005), or non-meaningful shapes (e.g., Unsworth et al., 2014; Fukuda et al., 2010; Babic et al., 2019). Thus, to date, it was not clear whether performance in a real-world object working memory task would also correlate with fluid intelligence scores. Given the involvement of concrete semantic knowledge when using real objects, which could reduce some of the core cognitive processes that are active in visual working memory tasks with simple features, it was plausible that object memory performance would not show a clear relation with fluid intelligence measures. Our results clearly show that this was not the case, as we found a reliable correlation between object working memory performance and fluid intelligence scores, indicating that the cognitive abilities captured by fluid intelligence tests are critical for actively maintaining real-world objects, similar to simple shapes. This result aligns with prior studies in verbal working memory that used stimuli like words in conceptual span tasks and found a relationship between working memory performance and fluid intelligence (e.g., Aizpurua & Koutstaal, 2010; Kane & Miyake, 2007). Our results extend this by showing that working memory for highly visually complex and meaningful stimuli similarly exhibits a strong and reliable relationship with fluid intelligence.

To further understand the implications of our findings, it is important to address why working memory performance might be correlated with fluid intelligence more generally. While the exact nature of the relationship is still under investigation, some previous research has argued that the capacity limit of working memory, that is, the maximum amount of information a person can actively maintain, is the most critical factor underlying its relationship with fluid intelligence because the more information one can store, the more information is available to be used for abstract reasoning tasks (e.g., Carpenter et al., 1990; Fukuda et al., 2010; Schubert et al., 2023). According to this view, our results would suggest that there may be shared processes that give rise to visual working memory capacities for real-world objects and colored circles, despite performance being significantly better for real-world objects. That is, the more information about colored circles a person can actively maintain, the more information they can also maintain about real-world objects. This is also supported by the correlation between the two working memory tasks we observe in the present study. However, some other research has challenged the view that these capacity limits per se underlie the relation (e.g., Engle et al., 1999; Hagemann et al., 2023). Specifically, some studies showed that questions on fluid intelligence tests that are more cognitively demanding, and thus should require more working memory storage to be solved, do not correlate more strongly with working memory capacity (Salthouse & Pink, 2008; Burgoyne et al., 2019; Wiley et al., 2011; Unsworth & Engle, 2005; but also see Frischkorn & Oberauer, 2021; Smolen & Chuderski, 2015). Instead, it has been suggested that other aspects of working memory tasks might be the crucial factors driving the correlation between working memory performance and fluid intelligence. These aspects include attentional control processes (Draheim et al., 2022; Shipstead et al., 2016), flexible binding of memoranda (Bateman & Birney, 2019), the usage of specific encoding strategies (Babic et al., 2019), or the ability to adapt and apply rules (Salthouse & Pink, 2008; Wiley et al., 2011; Duncan et al., 2012), potentially along with capacity itself (Unsworth et al., 2014). According to these accounts, our results suggest that these additional processes that are engaged during most working memory tasks are shared between remembering real-world objects and colored circles. For instance, although maintaining meaningful stimuli in visual working memory may activate additional conceptual knowledge relative to when maintaining abstract simple stimuli, the task still requires the same processing steps such as separately encoding the items, binding them to correct locations or sequences, protecting them against interference, actively maintaining them over a short period of time, and correctly retrieving the relevant memoranda at test. This perspective also aligns with previous findings that showed the involvement of similar active neural engagement during visual working memory maintenance of abstract and meaningful stimuli (Brady et al., 2016; Quirk et al., 2020; Asp et al., 2021; Thibeault et al., 2024). Thus, whether conceptual knowledge is involved or not, both working memory tasks are likely tapping into qualitatively similar active maintenance processes.

Interestingly, although not statistically significant, performance in the sequential working memory task for real-world objects showed a numerically higher correlation coefficient with fluid intelligence scores ($r = 0.38$) compared to performance in the sequential working memory task for colors ($r = 0.25$). A post-hoc power analysis indicates that more than twice as many participants would be required to find a reliable difference in correlation strengths based on the current results. From a theoretical perspective, it is not entirely clear why object working memory performance would correlate more strongly with fluid intelligence scores. Given the broad construct of fluid intelligence that includes multiple cognitive abilities, from abstract thinking to efficient problem-solving, one possibility is that people with higher fluid intelligence scores are also more effective at exploiting the benefits of real-world objects. In other words, people may differ in how they engage with the stimuli in the working memory tasks, and people that perform better on abstract visual reasoning tasks such as Raven's matrices test are also more effective in connecting object images to pre-existing conceptual knowledge. This possibility is further supported by the fact that individuals' differences in performances between working memory for real-world objects and colored circles correlated reliably with fluid intelligence scores. This finding reflects that the extent to which an individual's working memory capacity is increased for meaningful relative to simple visual stimuli is related to their fluid intelligence level. Thus, participants with higher fluid intelligence levels appear to derive more benefit from meaningful stimuli in enhancing their visual working memory performance. Future studies with larger sample sizes could test this hypothesis more directly, for example by probing participants' strategies and how they encode and process the objects.

Reliability of sequential and simultaneous visual working memory tasks

We also find that both sequential and simultaneous presentations of stimuli at encoding during the color working memory tasks resulted in significant correlations of similar magnitude with fluid intelligence and with each other. This is consistent with a recent study by Zhao and Vogel (2023) which found that individual differences in visual working memory performance are highly correlated between sequential and simultaneous presentations, demonstrating that both presentation formats are adequate in assessing visual working memory capacity and its relation to fluid intelligence. Interestingly, we observed that the visual working memory task for colored circles with simultaneous presentation resulted in the highest reliability score (0.79), followed by sequentially presented real-world objects (0.62) and then sequentially presented colored circles (0.29). Previous findings showed a greater benefit of sequential presentation for meaningful stimuli compared to abstract stimuli, as it allows for deeper semantic processing of each stimulus (Brady & Störmer, 2022; Chung et al., 2023a). Our data show that when stimuli are presented sequentially, real-world objects also result in higher reliability scores, comparable to the reliability level of simultaneous presentation of colored circles. In contrast, the reliability score for the color working memory task with sequential presentation was unexpectedly low. This outcome may stem from increased confusion or interference when perceptually similar simple features (like colors) are presented at the same location. This also aligns with previous findings that show the important role of spatial locations as indexing features to bind visual information in working memory (e.g., Schneegans & Bays, 2019; Swan & Wyble, 2014; Chen & Wyble, 2015; Tam & Wyble, 2022; Chung, Tam, et al., 2024). While the sequential color working memory task resulted in a low reliability score, which in turn makes it challenging to interpret correlation results using that specific task, we found a similar correlation with the much more reliable simultaneous color working memory task with spatial locations. Overall, this points to potentially significant considerations when thinking about how working memory capacity is measured. Future studies could systematically test how different presentation types and stimulus classes interact with the reliability of working memory tests.

Crystallized intelligence is not reliably correlated with visual working memory

We also tested whether visual working memory performances for colored circles and real-world objects are related to crystallized intelligence scores. While prior studies have found only weak relationships between crystallized intelligence and working memory (e.g., Salthouse & Pink, 2008; Buehner et al., 2006), especially when using abstract stimuli (Haavisto & Lehto, 2005; Dang et al., 2012; Dang et al., 2014), it seems plausible that working memory for real-world objects would have shown a different pattern, given that recognizing and understanding real-world objects relies on pre-existing semantic knowledge. However, we found no evidence of a correlation between the C-Test scores and working memory performances. It should be noted, however, that the C-Test in particular measures crystallized intelligence through language proficiency and it is unclear whether the C-Test accurately captures individual differences in semantic knowledge used when remembering real-world objects. Such verbal tests have been shown to correlate more strongly with verbal working memory tasks rather than visuo-spatial working memory tasks (Haavisto & Lehto, 2005; Dang et al., 2012; Dang et al., 2014). Previous studies have shown that real-world objects benefit visual working memory performance even when verbal strategies are controlled for (e.g., Brady et al., 2016; Chung et al., 2023b; Chung, Tam, et al., 2024; Starr et al., 2020). Additionally, a recent study showed that simply providing verbal category labels to unrecognizable shapes does not effectively enhance visual working memory performance (Chung, Williams, et al., 2024). Thus, while verbal knowledge is commonly associated with crystallized intelligence, it remains unclear whether it would serve as a critical underlying factor of object working memory performance. Furthermore, the current study used real-world objects that are frequently encountered in everyday life and thus likely do not vary substantially in their recognizability level or semantic meaningfulness across individuals. Previous research has demonstrated that not all objects are subject to the same amount of benefit in visual working memory. For instance, unfamiliar objects that are not commonly seen result in worse visual working memory performance compared to highly familiar objects (Starr et al., 2020; Li et al., 2020). Therefore, it is possible that variation in the familiarity or knowledge about the objects in a working memory task would also be related to individual differences in learned knowledge, and thus to some degree crystallized intelligence.

Previous studies reporting the meaningfulness benefit in visual working memory have argued that the benefit arises from the ability to rapidly connect visual inputs to pre-existing conceptual knowledge about what these objects are (Chung et al., 2024; Brady et al., 2024; Wyble et al., 2016) because perceptually complex stimuli that are not recognized as meaningful do not exhibit such improvement in performance (e.g., Asp et al., 2021; Chung et al., 2023b; Brady et al., 2016; Brown & Wesley, 2013; Alvarez & Cavanagh, 2004; Olson & Jiang, 2002). Therefore, it is plausible that the visually derived ability to recognize various objects, which is critical for the boost in working memory for meaningful stimuli, may correlate with crystallized intelligence test scores in a more visual domain (i.e., object recognition test). Thus, future investigations could incorporate crystallized intelligence tests that assess visual object recognition and also include images of objects in the working memory tasks that vary in recognizability (i.e., how they connect to conceptual knowledge) and familiarity across participants.

Limitation of the current study

One general caveat to consider in the current data is the potentially selective range of participants. For instance, all participants were young university students who generally scored highly on standardized tests (see Supplementary Materials). Indeed, the average Raven's test score was around 25, which is higher than scores reported in previous studies using a similar test to examine its relationship with working memory performance. While such a restricted participant range may have underestimated the correlations overall, we still found reliable correlations between the Raven's scores and all visual working memory measures. Importantly, this limitation in population would affect all comparisons equally. In addition, intelligence test scores were not largely skewed (-0.64 for the Raven's test scores and -0.32 for the C-Test scores). Nevertheless, future studies should consider testing a broader and more diverse population for improved generalizability of the results.

Summary

Our findings reveal a reliable correlation between individual differences in fluid intelligence and visual working memory performance for both abstract simple features and real-world objects. Our results also add to the emerging evidence that meaningful and familiar stimuli can enhance visual working memory processes. Collectively, these findings validate the use of real-world object stimuli to test visual working memory and indicate that remembering complex, meaningful stimuli and basic simple features share core cognitive processes that are related to fluid intelligence.

CRediT authorship contribution statement

Yong Hoon Chung: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kaira K. Shlipak:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis, Conceptualization. **Viola S. Störmer:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methdology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jml.2025.104648.

Data availability

All data are available online (https://osf.io/djg2b/).

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