1 Visual short-term memory for 3D shapes reveals similar properties to simple 2D features

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14 Authors Note

15 This work was supported by NSERC Discovery Grant (#435945) awarded to
16 SME. The authors would like to acknowledge Joseph Capozza, Koah Ing, and Brenda
17 deWit for their help collecting the data for this project.

Abstract

In the past two decades, significant advances have been made to understand the psychophysical properties of visual short-term memory (VSTM). Most studies, however, make inferences based on memory for simple surface features of 2D shapes. Here, we examined the role of object complexity and dimensionality on the psychophysical properties of VSTM by comparing orientation memory for 2D lines and complex 3D objects in a delayed-response continuous report task, where memory load (Experiment 1) or axis of rotation (Experiment 2) was manipulated. In both experiments, our results demonstrate an overall cost of complexity that affected participants raw errors as well as their guess rate and response precision derived from mixture modelling. We also demonstrate that participants' memory performance is correlated between stimulus types and that memory performance for both 2D and 3D shapes is better fit to the variable precision model of VSTM than to tested competing models. Interestingly, the ability to report complex objects is not consistent across axes of rotation. These results indicate that, despite the fact that VSTM shares similar properties for 2D and 3D shapes, VSTM is far from being a unitary process and is affected by stimulus properties such as complexity and dimensionality.

Keywords: VSTM, object complexity, modeling, 3D perception

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2 The temporary storage and manipulation of information, known as short-term
3 memory, has been studied extensively for the past few decades. One particular
4 characteristic of short-term memory that distinguishes it from other types of memory,
5 such as episodic and long-term memory, is its limited capacity to store information
6 (Baddeley, 2003; Cowan, 2001). In the visual domain, it has been repeatedly
7 demonstrated that increasing visual memory load results in a decrease in short-term
8 memory performance (Luck & Vogel, 1997; Vogel, Woodman, & Luck, 2001; Pashler,
9 1988). In one classic demonstration of this effect, Luck and Vogel (1997) conducted a
10 series of experiments in which they examined visual short-term memory (VSTM)
11 performance using a change detection paradigm. This experimental design consists of
12 presenting a display of stimuli for a brief period and, after a short delay, a similar display
13 would reappear in which the participants would indicate whether the display has changed
14 or remained the same. By varying the number of coloured squares to be remembered in
15 the memory display from one to twelve, Luck and Vogel demonstrated that participants
16 performed at near ceiling between 1 - 3 items, and would show a rapid decline in change-
17 detection accuracy when more than 4 items are presented. Interestingly, this pattern was
18 robust despite changing the stimulus complexity by presenting a conjuncture of different
19 features. Luck & Vogel (1997) concluded not only that VSTM has a capacity limit of
20 about 3-4 items, but also that VSWM stores items as integrated objects, meaning that
21 visual memories can be recalled with high accuracy, regardless of the number of features
22 each object has.

23 This capacity limit has also been supported by the observation of a potential
24 neural basis for a fixed memory capacity. Indeed, Vogel and Machizawa (2004) reported
25 that the contralateral delay activity (CDA), a sustained event-related potential that is
26 greater over the electrode sites contralateral to the target items during lateralized change
27 detection task, shows a steady increase in amplitude as set size increased, and reached a
28 maximum amplitude when 3 - 4 coloured squares had to be remembered. Similarly, fMRI
29 studies have demonstrated a comparable pattern in blood-oxygenation level dependent
30 (BOLD) activation in the intraparietal sulcus (IPS) as the number of simple items held in
31 memory increased, again showing an asymptote around 3 – 4 items (Todd & Marois,

2004; Xu & Chun, 2006; but see Bays, 2018). Together with the behavioural reports, these studies gave rise to a discrete representation view of memory storage, where information associated with objects is stored with high precision in a limited number of “slots” (Vogel et al., 2001).

To better investigate the nature of VSTM representations – specifically the degree of noise or precision with which information is represented – a number of new psychophysical approaches have been taken in recent years. Building off of a continuous recall procedure developed by Wilken and Ma (2004), Zhang and Luck (2008) devised a method to investigate both the number of items stored in VSTM, as well as their precision. In the continuous response task, the memoranda consist of features that vary continuously along a circular dimension (e.g., colour or orientation). Then, in the approach taken by Zhang and Luck (2008), the data were analyzed according to two principles: First, given the chance to freely report the exact feature of the memorized item, participants reporting an item that is successfully encoded and stored in memory should report a value close to the target feature (i.e., with low error). Over several trials, these responses will be normally distributed around the target value where the width of this distribution represents the precision of one’s memory. Second, when an item is not stored in memory, participants should pick a random feature value, which will generate a uniformly distributed pattern of responses over the course of an experiment.

Consequently, Zhang and Luck (2008) applied a mixture model (i.e., circular normal and uniform) to the participants’ responses. They reported that the prevalence of guesses increased significantly when the number of items to be remembered was above the putative 3 – 4 items capacity limit. Furthermore, the precision of the memories, represented by the width of the normal response distribution, remained unchanged across set sizes greater than 3 items, which suggests that the quality of the remembered items were unaffected by the increase in set size. Therefore, by moving away from a dichotomous change detection paradigm to a continuous response paradigm, Zhang and Luck (2008) were able to isolate both the number and precision of discrete representations stored in VWM.

Although influential, a number of recent findings have challenged the validity of discrete memory models. In particular, resource-based models postulate that limits in

memory capacity exists as a result of noise in the neural signal, where increasing the number of items presented divides memory resources resulting in a decrease in the quality of memory representations (Wilken & Ma, 2004; Bays & Husain, 2008; Tomić & Bays, 2018). In a series of experiments that used both change-detection and continuous report, Wilken and Ma (2004) applied signal detection theory models that account for neural noise and a simple decision rule, and demonstrated that not only did these models accurately describe the data, but also that they could do so without including discrete ‘slots’ or an upper limit on the number of items that could be stored. Furthermore, Bays and Husain (2008) demonstrated that participants’ error on a test of short-term memory for locations and orientations decreased as a function of set size, and was best described as a saturation function without discrete capacity limits. Thus, these results suggest VWM capacity is better described as continuous resource that can be allocated to all items presented, and that the noise (or inverse precision) of representations increases concomitant with the number of items to be stored. Furthermore, Ma, Husain and Bays (2014) suggested that the load-dependent modulation of the CDA (Vogel & Machizawa, 2004) and the changes in BOLD signals in the intraparietal sulcus (Todd & Marois, 2004; Xu & Chun, 2006), which was presumably believed to support the discrete memory hypothesis, appear to also exhibit a saturation function that is characterized by behavioural performance (Bays & Husain, 2008; Emrich, Lockhart, & Al-Aidroos, 2017; van den Berg & Ma, 2014). This reinterpretation is supported by a recent study by Bays (2018) where the re-evaluation of the original BOLD signals (Todd & Marois, 2004; Xu & Chun, 2006) reveals a better fit for a continuous resource model perspective of VSTM, whereas the fits were equivocal between the discrete and resource models for the modulation of the CDA amplitude (Vogel & Machizawa, 2004).

While the debate over how best to characterize the nature of VWM capacity limits continues (Suchow, Fougner, Brady, & Alvarez, 2014; M. Schurgin & Brady, 2018; van den Berg & Ma, 2018), one limitation common to these previous studies is that they have all been performed using simple 2-dimensional stimuli that vary in one or two key surface feature. Thus, regardless of which model best describes VWM performance, it remains possible that different effects might be observed for more complex stimuli. Moreover, although these tightly controlled stimuli allow us to probe the nature of VWM

1 representations, one might question the ecological validity of these experiments, when the
2 day-to-day application of VSTM is for more complex stimuli.

3 A number of studies have investigated the effect of stimulus complexity on the
4 properties of VSTM. As mentioned earlier, the idea of discrete memory representations
5 introduced by Luck and Vogel (1997) arose in part because presenting a conjunction of
6 different features did not impact memory performance. However, this phenomenon has
7 not been reliably replicated (Delvenne & Bruyer, 2004; Wheeler & Treisman, 2002). In a
8 series of experiments, Wheeler and Treisman (2002) demonstrated that items held in
9 memory would only compete along their common feature dimension (e.g. orientation,
10 shape, colour), suggesting that separate memory capacity exists in parallel for different
11 feature dimensions. They were unable to replicate Luck and Vogel's (1997) results and
12 demonstrated that, when participants are required to bind the various features, integrated
13 memory items were more susceptible to interference (Marshall & Bays, 2013).

14 In addition to controlling the number of features contained within a visual object,
15 several studies have also examined the effect of stimulus complexity on VWM
16 performance. Alvarez & Cavanagh (2004) ranked the complexity of a number of different
17 stimuli (e.g. squares, letters, random polygons, shaded cubes) based on a visual search
18 processing speed and showed a direct inverse relationship between complexity and
19 memory capacity as assessed by change detection. Hence, these results demonstrate a
20 cognitive trade-off, where greater VSTM resources are required when complex stimuli
21 are encoded, resulting in the storage of fewer items. Other studies examined change
22 detection with similar simple and complex objects and concluded that although memory
23 load could affect the resolution with which information is stored in memory, information
24 is stored in a fixed number of discrete slots, regardless of complexity (Awh, Barton, &
25 Vogel, 2007; Barton, Ester, & Awh, 2009).

26 There have also been a few attempts to investigate short-term memory for more
27 complex, naturalistic stimuli. Indeed, studies have reliably demonstrated that more faces
28 can be held in short-term memory than other complex non-face stimuli (Curby &
29 Gauthier, 2007) or classic short-term memory stimuli such as line orientations (Jiang,
30 Shim, & Makovski, 2008). Lorenc et al. (2014) used memory recall for faces in a
31 continuous response paradigm and found that upright faces were recalled with greater

precision than inverted faces. Similar effects have been observed for own-race compared to other-race faces (Zhou, Mondloch, & Emrich, 2018), suggesting that the holistic integration of face stimuli, rather than complexity per se, may confer this particular advantage (Curby & Gauthier, 2007). Comparable findings are observed with other objects with which individuals show expertise. Xie and Zhang (2017) demonstrated that individuals who are familiar with a certain generation of Pokémon characters have a clear memory advantage over unfamiliar (more recent generation) characters. Prior experience with certain stimuli, such as familiarity or expertise, seems to fundamentally change the psychophysical properties of the short-term memory process at play.

There is also neural evidence that stimulus complexity affects the ability to encode and store information in VWM. Indeed, Luria et al. (2010) showed a larger CDA amplitude during the retention of complex polygon stimuli in comparison to coloured squares, which is indicative of greater short-term memory demands as a function of stimulus complexity. Similarly, Wilson, et al. (2012) demonstrated that while the CDA amplitude in some channels appeared to track with the number of discrete objects, at other channels the amplitude appeared to reflect the number of features contained within an object. This finding is mirrored by fMRI BOLD signal in the IPS. Specifically, while the inferior aspect of the IPS appears to reflect the number of items attended at different locations, the superior IPS appears to reflect the amount of featural information maintained in VWM (Xu & Chun, 2006; Xu, 2007). Thus, although it is clear that VWM can be affected by feature and object complexity, it is not clear whether this has any effect on how to describe the nature of VWM capacity limits (e.g., whether they are discrete or continuous). Interestingly, the short-term memory advantage conferred by recognizable or familiar objects does not appear to be the result of a change in the underlying networks involved, but rather from a more robust encoding of the memorandum as described by a recent fMRI study by Veldsman, Mitchell, & Cusack (2017).

To summarize, although significant advances have been made in recent years in an attempt to adjudicate between different models of VWM capacity limits, as well as the neural mechanisms that support them, these studies have tended to use simple surface features of two-dimensional stimuli, which may limit their legitimacy both as models of

memory performance, and as ecologically valid stimuli. Similarly, although some studies have examined VWM for more complex stimuli, these studies have relied on high-threshold change-detection approaches, or on stimuli that are affected by familiarity and expertise, and thus the effect of object complexity on memory precision vs. capacity remains somewhat unclear. Consequently, the aim of the present study is to examine the role of stimulus complexity on the psychophysical properties of VSTM representations. To examine complexity using stimuli that could be easily controlled while still remaining unfamiliar, we compared continuous recall performance for 2D lines to that of novel 3D shapes consisting of an assembly of cubes. Experiment 1 compared the psychophysical properties (i.e. raw error, guess rate, and precision) of short-term memory for the orientation of a complex objects and simple lines across multiple set sizes. We also examined the goodness of fit of a number of popular models of VSTM capacity limits for both kinds of stimuli. Experiment 2 compares memory of orientation of a simple line to orientation of a complex 3D objects over 3 different axes of rotation. By examining memory performance for 3D objects, these experiments provide an important first step in establishing a more ecologically valid model of VSTM capacity limits.

Experiment 1

Methods

Participants. Forty-four (12 males; normal or corrected-to normal vision, 17-32 years of age, $M = 19.54$) Brock university students participated in the experiment and were compensated with course credits or \$10/hr. Participants were screened upon arrival for colour-blindness using Ishihara's 38 plates test. All procedures were approved by the Brock University Research Ethics Board.

Apparatus. Participants completed the tasks on a 20-in. flat LCD with a resolution of 1600-1200 ppi and a refresh rate of 60 Hz. Stimuli were generated and presented using MATLAB (mathworks.com) software along with the Psychophysics Toolbox extension (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997).

Stimuli. The simple 2D stimuli used in our short-term memory task consisted of a line 4.5° of visual angle long and 0.45° wide. The orientation of this simple stimulus was manipulated from the center point of the stimulus, and could span the full 180° of possible positions. The 3D complex shape version of the short-term memory task used a

selection of 25 objects constructed from an arrangement of 9 cubes with 4-5 90° bends. To ensure cohesion and create one solid object with no floating parts in a given shape, at least one face of every cube faced another cube. These shapes were rendered using OpenGL functions of the Psychophysics Toolbox MATLAB extension. Following creation, they were visually inspected to ensure that they possessed unique and distinguishable features from one another. Depending on their orientation, these 3D complex shapes can be between 1.32 – 2.6 visual degrees in any direction. At the beginning of each trial, one of the 25 3D objects were randomly selected (without replacement), each of which was assigned a random orientation, and were rotated only over the z-axis across set sizes. In a given multi-item trial, simple or complex stimuli were oriented at least 30° from one another.

Procedure. Participants performed a continuous-recall task in which the memory sample varied in set size, with simple or complex objects presented in separate tasks (see Figure 1A). A trial would begin with the serial presentation of 1, 2 or 4 stimuli (simple 2D line or 3D shape) where each stimulus would be displayed for 500 ms, with a 500 ms inter-stimuli interval (ISI) based on the sequential set size design described by Gorgoraptis, Catalao, Bays, & Husain (2011). Each object's orientation varied along the z-axis and the colour of each object randomly selected between red, blue, green, or yellow. Following a 500 ms delay, one of the colored objects in the sequence reappeared during the probe. Using the mouse, participants reported the orientation of the probed item by rotating the object along the z-axis and clicking to report their response. Each trial was separated by a 1,000 ms inter-trial interval (ITI). The order of the colors and the probe position in the sequence were counter-balanced. Complex 3D objects were assigned a random orientation over the x-, y-, and z-axis at the beginning of a given trial and it would only vary across the z-axis between sample and probe. Prior to beginning the simple and complex continuous report tasks, participants were trained on a series of practice trials until they felt comfortable with the task. Participants completed 80 trials for each set size (i.e. 1, 2, or 4), for a total of 240 trials each of simple 2D and complex 3D object orientations. To reduce the primacy effect, 23 participants began the experiment with line orientation task first, while the rest began with the complex 3D shapes task. All 3D stimuli and stimulus presentation paradigm for Experiment 1 and 2

described in this article are available online in an Open Science Framework repository (<https://osf.io/9cdqz/>).

After the short-term memory tasks were completed, participants were then required to complete a computerized version of the Vividness of Visual Imagery Questionnaire (VVIQrv) (Marks, 1973; McKelvie, 1995) as well as the Object-Spatial Imagery and Verbal Questionnaire (OSVIQ) (Blajenkova, Kozhevnikov, & Motes, 2006). As part of a different research question, the score on these questionnaires were used to correlate between memory performance and subjective measures of imagery quality and strategy. Although the scores from these questionnaires are not reported here, these analyses did not yield any significant correlations.

Analysis. One measure used to assess participants' performance was raw response error, which is calculated by taking the standard deviation of the absolute angular distance between the target and reported orientation. This measure was computed for each condition and participant. Raw error is inversely related to response precision, where a lower value corresponds to a response closer to the target orientation. As this measure has been demonstrated as the most reliable measure of performance (see van den Berg & Ma, 2018, about summary statistics; also Ma, 2018) all reported correlations used raw error as a measure of participants' performance.

Performance was also modeled according to the two-component Mixture Model proposed by Zhang and Luck (see Zhang & Luck (2008), for a full description of the model). The model assumes that the overall distribution of participants' responses come from two types of responses: in trials where participants fail to recall a probed item, participants will guess by picking a random location on the wheel, which in turn will produce a uniform distribution – the greater the proportion of guesses, the greater the height of the uniform distribution. Conversely, in trials where participants successfully encode and store an item in memory, their responses will cluster around the target value and will produce a Von Mises distribution (i.e. circular analog to the Gaussian distribution) centered at the target item. The standard deviation of the latter distribution is used as a measure of the precision of participant's memorized item. Therefore, a participant's pattern of responses is produced from the contribution of these two types of trials: guesses and target responses. Using the maximum likelihood estimation (MLE),

the distribution of raw error is decomposed into the guess rates (P_g), target rate (P_T) and precision (SD) for each condition. Since the guess and target rate are complementary (i.e., $P_g + P_T = 1$), only the proportion of guesses will be reported, along with precision. The parameters of the mixture models were computed using the Memtoolbox Matlab extension (see Suchow, Brady, Fougner, & Alvarez, 2013; memtoolbox.org).

For statistical comparisons, a 2 (simple vs. complex) x 3 (set sizes of 1, 2, or 4) within-subject frequentist and Bayesian ANOVA was performed on the measures of raw error, mixture model guess rate, and mixture model precision. All statistical analyses were computed using JASP (JASP Team, 2018). Note that, in the frequentist analysis, degrees of freedom were corrected using Greenhouse-Geisser estimate whenever the assumption of sphericity was violated. To explore the interaction between object complexity and set size, two one-way repeated measures ANOVAs were carried to evaluate the effect of set size on each object complexity separately as well as three paired t-test comparisons to evaluate the effect of complexity within each set sizes. Bayesian repeated measures ANOVA were also computed to provide more information about the strength of the evidence in favour of the null or alternative hypotheses. For simplicity's sake, we will only be reporting the Bayesian Factor as it pertains to the alternative hypothesis (i.e., BF_{10}). Note that Bayesian ANOVA compares models and, unlike the frequentist approach, it is not investigating effects. In other words, Bayesian ANOVA investigates the strength of the evidence in support of all possible models (i.e. null, main effect 1, main effect 2, both main effects, and both main effects with an interaction). For each Bayesian ANOVA, the prior term was set using JASP's default Cauchy width and we report the best-supported model only. Finally, to determine the extent of ones' ability to perform this short-term memory task with simple or complex stimuli, we performed pairwise Pearson correlations and Bayesian correlations.

Model comparison. To compare the ability of different models of VSTM to describe the change in performance across loads, we also conducted a factorial comparison of short-term memory models using the procedure described by van den Berg et al. (van den Berg, Shin, Chou, George, & Ma, 2012; van den Berg, Awh, & Ma, 2014; ronaldvandenberg.org; see also Emrich, Lockhart, & Al-Aidroos, 2017). Specifically, we compared the goodness of fit of some of the leading short-term memory models using

Akaike (AIC: Akaike, 1974) and Bayesian information criterion (BIC: Schwarz, 1978) as penalty-based model comparison measures. The models that were compared here, as described by van den Berg et al. (2014), were the fixed-precision (FP) (Luck & Vogel, 1997), slot+averaging (SA) (Zhang & Luck, 2008), equal precision (EP) (Bays & Husain, 2008), and variable precision (VP) (van den Berg et al., 2012; Fougne et al., 2012). The first two models assumed that a fixed amount of items were remembered (-F), denoted as FP-F and SA-F, whereas the EP model assumed that all items presented were remembered (-A). Finally, we compared the VP model with both assumptions independently. We compared a total of 5 different models (i.e. FP-F, SA-F, EP-A, VP-A, and VP-F) on participants' pattern of response for simple and complex objects.

Results

The aim of the first experiment was to determine how memory load affects the properties of VSTM in a continuous recall task when participants are required to remember simple or complex stimuli. To do so, participants were presented serially 1, 2, or 4 stimuli that varied in orientation (180° for simple line stimuli or 360° complex 3D objects) and were required to report the orientation of the probed item. We first examined participants' raw error (derived from the angular difference between the target orientation and the reported orientation). Participants responses were also modeled according to Zhang and Luck's (2008) two-component mixture model to obtain participants' proportion of guesses and precision. Raw error, guess rate and precision were analyzed independently using repeated ANOVA with within subject factors of stimulus complexity (simple 2D and complex 3D) and set size (1, 2, or 4 items). Finally, we also performed a factorial comparison of four popular models of VSTM for both kinds of stimuli.

Figure 1. (A.) A schematic representation of the delayed-response task used in experiment 1. Participants were exposed to 1, 2, or 4 objects (simple or complex) and were required to report orientation of a probed object after a short delay. Participants' mean raw error (B.), guess rate (C.) and precision (D.) comparison between the report of simple or complex object orientation across set size. Error bars represents standard error. (E.) Scatterplot of the mean raw error for each individual for the simple 2D or complex 3D shape orientation tasks from Experiment 1 (set size 1) and 2 (z-axis rotation) combined (N = 92). (F.) Scatterplot of the mean raw error between simple and complex objects across set size 2 (black) and set size 4 (grey).

Raw error. As our first examination of participants' performance, 2 (simple line vs. complex shape stimuli) x 3 (set size of 1, 2, or 4 items) repeated measure frequentist and Bayesian ANOVAs were conducted to evaluate the variability in the standard deviation of the absolute angular difference between the target and reported stimuli orientation (i.e. raw error) (see Figure 1B). The Bayesian analysis demonstrates that the model that includes complexity of the object and set size without interaction offers the best fit, $BF_M = 20.63$, $BF_{10} = 1.04e^{72}$. We replicated previous reports effect of set size $F(2,82) = 81.44$, $p < .001$, $\eta^2 = 0.67$, where post-hoc comparisons using Bonferroni correction reveals that participants report the target item with more error when they are required to remember 4 items over 2, $M_{diff} = 8.636^\circ$, $SD = 2.20^\circ$, $BF_{10} = 2.16e^{12}$, 2 items over 1, $M_{diff} = 5.132^\circ$, $SD = 2.35^\circ$, $BF_{10} = 8.39e^3$, and 4 items over 1, $M_{diff} = 13.77^\circ$, $SD = 2.13^\circ$, $BF_{10} = 1.34e^{20}$, where all $ps < .001$. Consistent with the literature, we demonstrate again that performance declines as the number of item held in memory increases regardless of the complexity of the object remembered. Moreover, we found a significant main effect of stimulus complexity, $F(1, 41) = 404.3$, $p < .001$, $\eta^2 = 0.91$, where there is a significant increase in raw errors when participant reported complex items, $M_{diff} = 22.76^\circ$, $SD = 1.32^\circ$. These results support the idea that complexity increases the amount of error in VSTM. The absence on an interaction effect between shape complexity and set size ($F(2,82) = 1.913$, $p = .154$, $\eta^2 = 0.045$) suggests that the memory of simple and complex objects are encoded and stored in a similar fashion. Altogether, these results support the idea that the memorization of complicated stimuli requires greater cognitive resources, but that the effect of load and complexity are independent. Indeed, it appears that there is a fixed cognitive cost in memorizing complex 3D object that works independently from increases in set size.

To investigate whether short-term memory for line orientation is associated with that for the orientation of complex items, we calculated simple-complex object pairwise Pearson's correlations and Bayes correlation factors of the raw error for each level of memory load. Given that the set size 1 condition in Experiment 1 for both the simple and complex tasks are the identical to the z-axis rotation in Experiment 2, we aggregated the results to yield a sample of 92 participants for this correlation only. This combined correlation displayed in Figure 1E between raw error of simple and complex shows a

significant relationship, $r_{ss1} = .381, p < .001$ and Bayes Factor provides very strong evidence in favour of the correlation ($BF_{10} = 110.6$). As is displayed in Figure 1F, the correlations between raw error for simple 2D and complex 3D objects for set size 2 and 4 are significantly correlated with each other, $r_{ss2} = .396, p = .009$; $r_{ss4} = .417, p = .006$ and Bayes factor demonstrates a greater likelihood against the null hypothesis across all set sizes, SS2: $BF_{10} = 4.998$; SS4: $BF_{10} = 7.335$. These results indicate that one's ability to remember the orientation of simple stimulus is strongly associated with the memory of more complex stimulus. This is particularly true for set size 1 as 30.9% of the variance is accounted for in this correlation and that Bayes factor shows very strong evidence against the null.

Mixture Model.

Guess rate. Next, we examined the effect of stimulus type and set size on the proportion of guesses derived for the two-component mixture model (Figure 1C). In addition to main effects of both size and complexity, $F(1,41) = 70.89, p < .001, \eta^2 = 0.635$; $BF_M = 1.71e^{-12}, BF_{10} = 5.12e^{25}$ and $F(2,82) = 54.25, p < .001, \eta^2 = 0.570$; $BF_M = 9.51e^{-36}, BF_{10} = 283.98$, respectively, a repeated measures frequentist and Bayesian ANOVA revealed a significant interaction between set size and shape complexity, $F(2,82) = 48.818, p < .001, \eta^2 = 0.544$; $BF_M = 3.06e^7, BF_{10} = 1.20e^{38}$. We therefore investigated the simple effect of set size on the proportion of guesses using repeated measures ANOVA for simple and complex shapes separately. The proportion of guesses did not differ across set size for simple object, $F(2,82) = 0.778, p = .463, \eta^2 = 0.019$, but it did reach significance for complex objects, $F(2,82) = 60.781, p < .001, \eta^2 = 0.597$. Post-hoc t-test comparisons with a Bonferroni correction between the different set sizes for the complex object condition reveal a greater proportion of guesses when 4 objects were presented than 2, $M_{diff} = 14.2\%, SD = 23.7\%, p < .001, BF_{10} = 8.11e^5$, or 1, $M_{diff} = 22.5\%, SD = 28.4\%, p < .001, BF_{10} = 1.61e^{10}$, and between 2 objects compared to 1, $M_{diff} = 8.30\%, SD = 19.4\%, p < .001, BF_{10} = 1.58e^2$. We also conducted pairwise t-tests to investigate the effect of complexity across each set sizes. Overall, simple objects showed a significantly (all $p < .001$) lower proportion of guesses

than complex objects across set sizes, SS1: $M_{diff} = 11.3\%$, $SD = 16.0\%$, $BF_{10} = 1.23e^3$; SS2: $M_{diff} = 18.6\%$, $SD = 23.4\%$, $BF_{10} = 2.81e^4$; SS4: $M_{diff} = 33.7\%$, $SD = 36.5\%$, $BF_{10} = 1.37e^{11}$. The proportion of guesses across set sizes for the simple objects reported here shows no difference between set sizes, whereas there is a clear increase in guessed responses as set size increases.

Target precision. The second component of the mixture model consists of the precision in participants' response. Although there was a main effect of set size, $F(1.29, 52.73) = 133.01$, $p < .001$, $\eta^2 = 0.764$; $BF_{10} = 5.12e^{25}$, there was no effect of complexity, $F(1, 41) = 1.141$, $p = .292$, $\eta^2 = 0.027$; $BF_{10} = 283.98$. Repeated measures frequentist and Bayesian ANOVAs did, however, reveal a significant interaction between set size and stimulus type, $F(1.45, 59.29) = 3.93$, $p = .037$, $\eta^2 = 0.087$; $BF_{10} = 3.735e^{22}$. We investigated the simple effect of set size on simple and complex object separately using repeated measure ANOVAs. Simple objects showed significant differences in precision across set size, $F(1.52, 62.10) = 127.4$, $p < .001$, $\eta^2 = 0.757$, where post-hoc t-test comparisons (Bonferroni corrected) reveal greater precision in set size 1 than set size 2, $M_{diff} = 4.32^\circ$, $SD = 11.30$, $p < .001$, $BF_{10} = 1.25e^3$, and set size 4, $M_{diff} = 19.58^\circ$, $SD = 22.48$, $p < .001$, $BF_{10} = 6.72e^{12}$, as well as greater precision in set size 2 than 4, $M_{diff} = 15.26^\circ$, $SD = 18.99$, $p < .001$, $BF_{10} = 2.35e^{11}$. Repeated measures ANOVA looking at complex objects reveals a significant differences across set sizes, $F(1.25, 51.04) = 44.28$, $p < .001$, $\eta^2 = 0.519$, where decreased precision is observed when 4 objects were presented than 2, $M_{diff} = 10.53^\circ$, $SD = 14.90^\circ$, $p < .001$, $BF_{10} = 9.56e^3$, or 1, $M_{diff} = 14.88^\circ$, $SD = 18.13^\circ$, $p < .001$, $BF_{10} = 6.35e^6$, and between 2 objects compared to 1, $M_{diff} = 4.35^\circ$, $SD = 7.66^\circ$, $p < .001$, $BF_{10} = 1.39e^4$.

Finally, to investigate the effect of complexity across each set size on the precision of participants' responses, we also conducted pairwise t-tests. Across set sizes, no significant differences in precision were observed between simple and complex objects at any set size, SS1: $M_{diff} = 3.40^\circ$, $SD = 9.43^\circ$, $t(41) = 1.995$, $p = 0.053$, $d = 0.308$, $BF_{10} = 1.25e^3$; SS2: $M_{diff} = 3.43^\circ$, $SD = 9.90^\circ$, $t(41) = 1.734$, $p = 0.090$, $d = 0.268$, $BF_{10} = 16.72e^{12}$; SS4: $M_{diff} = 1.31^\circ$, $SD = 12.29^\circ$, $t(41) = 0.539$, $p =$

0.539, $d = 0.083$, $BF_{10} = 2.35e^{11}$. Thus, although there was a significant interaction between complexity and set size, with no main effect of object complexity, this finding was driven by only marginal effects of complexity at loads 1 and 2. Contrary to the results of the raw error and mixture model guess rate, these results provide evidence that the precision of memorized items is largely unaffected by the complexity of the object stored.

Model comparison. To further examine how the short-term memory of simple items maps on to more complex stimuli, we compared how different models of memory capacity can account for participant's responses. For example, some models have suggested that more complex stimuli may limit the number of items stored in memory, whereas others argue complexity occupies additional resources. By directly comparing how these models compare for simple and complex stimuli, it may reveal evidence in support of particular models of memory capacity.

The results of the model comparison are summarized in Table 1. Given that AIC and BIC values cannot be compared across datasets, only across models, it is not possible to directly compare the fits between simple and complex objects. Comparing within stimulus type, however, reveals a consistent pattern. There is stronger evidence in favour of the variable precision model over other models when participants are presented with simpler 2D stimuli, as indicated by lower AIC and BIC values, consistent with previous findings (Emrich et al., 2017; Fougine, Suchow, & Alvarez, 2012; van den Berg et al., 2014). Interestingly, the variable precision model, without a fixed capacity, appears to also best describe the change in performance for the complex objects (and by the same magnitude), suggesting that short-term memory precision varies greatly from trial-to-trial regardless of the shape complexity. Thus, while we are limited in the conclusions we can draw from this kind of model comparison, these results suggest that models of VSTM capacity limits perform similarly across simple and complex objects.

Table 1

Mean and Standard Error (in brackets) AIC and BIC Values of VSTM Model Fit for Simple and Complex Objects

AIC	BIC
-----	-----

Simple				
Fixed Precision (F)	191.24	(29.82)	198.20	(29.82)
Slot +Averaging (F)	169.38	(30.48)	179.83	(30.48)
Equal Precision (A)	157.90	(30.55)	168.34	(30.55)
Variable Precision (A)	141.33	(31.23)	155.25	(31.23)
Variable Precision (F)	143.20	(31.20)	160.60	(31.20)
Complex				
Fixed Precision (F)	530.27	(24.76)	537.23	(24.76)
Slot +Averaging (F)	525.10	(25.68)	535.54	(25.68)
Equal Precision (A)	538.21	(24.62)	548.66	(24.62)
Variable Precision (A)	462.10	(27.30)	476.03	(27.30)
Variable Precision (F)	463.85	(27.30)	481.25	(27.30)

1 *Note.* The VSTM models were assessed assuming that either all items (A) presented or a
2 fixed amount (F) of items are remembered.

3 **Discussion**

4 In this first experiment, we investigated the effect of object complexity on raw
5 error, proportion of guesses and memory precision using a standard memory load
6 manipulation. Our results demonstrate that short-term memory performance is similarly
7 affected by load for both simple lines and complex 3D objects, save for a few small
8 differences. We compared popular models of VSTM for both kinds of stimuli, with
9 similar performance for both simple and complex 3D objects suggesting shared
10 mechanisms limiting VSTM capacity.

11 Examining raw error revealed that memory performance was similarly affected by
12 load for both simple and complex 3D objects. Critically, memory performance was worse
13 overall for the complex objects. This finding is consistent with previous studies which
14 have demonstrated that object complexity affects VSTM performance (Alvarez &
15 Cavanagh, 2004; Delvenne & Bruyer, 2004; Rademaker, Park, Sack, & Tong, 2018;
16 Wheeler & Treisman, 2002). We believe this is the first study to directly compare the
17 effects of complexity in a recall task, without the stimuli being affected by familiarity and

1 experience. Thus, we establish here that the effect of complexity on VSTM performance
2 is not restricted to change-detection tasks, which could be affected by differences at the
3 comparison stage (Awh et al., 2007; Barton et al., 2009), or relying on high-threshold
4 responses. Importantly, there was no observed interaction between object complexity and
5 set size. Thus, while both manipulations appear to impact cognitive load, they appear to
6 do so independently. We also show that the ability to perform this VSTM task is
7 moderately correlated across stimulus type, demonstrating a reliance on a shared process.
8 Thus, although partially independent, the ability to remember either stimulus is mediated
9 partly by overlapping mechanisms. The implications of this partial independence will be
10 discussed further in the General Discussion.

11 Using the two-component mixture-model devised by Zhang and Luck (2008), we
12 also examined the effect of complexity on guesses and memory precision. Here, the
13 results differ slightly from those of raw error, as significant interactions between
14 complexity and load were observed in the guess rate and the amount of precision;
15 furthermore, the estimates of memory precision appear not to have been affected by
16 complexity at all. The straightforward interpretation of these findings is that while
17 complex objects are remembered with a similar degree of precision, complex objects are
18 much less likely to be stored in memory. In other words, it is possible that this reflects the
19 fact that complex objects occupy additional storage “slots”, resulting in a reduction in the
20 number of items that can be stored.

21 There are several reasons to be cautious of this interpretation, however. One,
22 numerous models have called into question whether guesses are real responses. For
23 example, these apparent responses could be the result of variability in response precision
24 (Fougnie et al., 2012; van den Berg et al., 2012), or a result of simple psychological
25 scaling (M. W. Schurgin, Wixted, & Brady, 2018). Second, some have suggested that
26 making comparisons of “summary statistics” is a flawed approach (Ma, 2018; van den
27 Berg & Ma, 2018). Third, the formal model comparison (Table 1) does not support a
28 model in which a fixed number of “slots” exist over which resources are averaged, and
29 indeed provides negligible evidence for a fixed number of storage “slots”. Fourth, this
30 effect failed to replicate in Experiment 2 (load 1 only). Thus, while we present the results

here for completeness, we do not believe strong conclusions can be drawn from these mixture model results.

Although the formal model comparison also provides evidence suggesting similar mechanisms affect VSTM for both simple and complex objects, here too there are limitations. First, as mentioned above, it is not possible to directly compare between the different data sets (i.e., between simple and complex). Thus, we are limited to drawing indirect conclusions from the similarity in which models were best fit to the data.

Second, we only tested a limited number of set sizes. Thus, it is possible that with a more extensive set of loads, different models may have been a better fit to the data. Finally, it is possible that other models may be a better fit to the data than the ones tested here. While our results are consistent with several studies suggesting that variable precision models without a fixed capacity best describe changes in memory performance across loads (Emrich et al., 2017; van den Berg et al., 2014, 2012), several new models have been developed within the past few years (Hardman, Vergauwe, & Ricker, 2017; Stengård & Berg, 2019). Thus, we do not believe these results definitively rule out the possibility that other models may be a better fit to the data than the models tested here; instead, we believe that the results demonstrate that complex 3D shapes perform similarly across model types, suggesting that they are a viable stimulus for delineating between potential mechanisms limiting VSTM, while providing a potentially more ecologically valid stimulus than simple features.

Experiment 2

Experiment 1 demonstrated that short-term memory for complex 3D shapes exhibits similar behaviour as compared with simple 2D stimuli, particularly across raw error and models of memory capacity. This similarity is perhaps not surprising given that both tasks involved rotating the objects over the same dimension (i.e., around the z-axis). However, working with 3D objects allows for rotation over additional planes. To our knowledge, however, it has not been previously investigated whether memory for the features of visual objects are represented with similar precision across all dimensions. Consequently, the aim of Experiment 2 was to examine VSTM for complex objects in a continuous response task over multiple dimensions.

Methods

Participants. Forty-eight (7 males; normal or corrected-to normal vision, 18-32 years of age, $M = 19.62$) Brock university students were recruited for the second experiment. As in Experiment 1, participants were compensated with course credits or \$10/hr and they were screened for colour-blindness.

Stimuli & procedure. The second experiment is the same as Experiment 1 with the following exceptions: participants are required to remember the orientation of a single item per trial and the complex object could be manipulated over one of three different axes of rotation (i.e. x-, y-, or z-axis; see Figure 3A). Participants completed 80 trials for each 3D orientation (i.e. x-, y-, or z-axis), for a total of 240 intermixed trials. Since a 2D line can only be manipulated over the z-axis, participants were required to complete only 80 trials. To reduce the primacy effect, 24 participants began with simple 2D line short-term memory task first followed by the complex 3D object while the other 24 participants began with the 3D shapes first.

Following the short-term memory tasks, participants were required to complete a computerized version of Sheppard and Metzler (2008) imagery task and the VVIQ-rv and OSVIQ. This task and two questionnaires were part of a different project and will not be reported here.

Analysis. As in Experiment 1, we based our analyses on participants' raw error (SD) as well as the guess rate and precision parameters derived from modeling the distribution of participants' responses the two-components mixture model (Zhang & Luck, 2008) obtained by modeling the distribution of participants' responses. In the first set of comparisons, we evaluate the error between simple lines rotated over the z-axis against all axis rotations of the complex shapes using frequentist and Bayesian t-tests. Then, we compared the different axes of rotations within the complex conditions using a one-way repeated measure frequentist ANOVA, where Greenhouse-Geisser correction is applied when the sphericity assumption is violated. Post-hoc frequentist analyses were conducted by carrying t-tests with a Bonferroni correction. Repeated measure Bayesian ANOVA were also carried out, where the posterior odds were corrected using a fixed prior of 50% and individual t-tests were based on a default Cauchy prior. Here again, all statistical analyses were computed using JASP (JASP Team, 2018).

Figure 1. (A) A schematic representation of all three axes of 3D rotations and the delayed-response task used in experiment 2, which was exactly the same as load 1 condition in experiment 1 with the exception that the complex 3D object can be rotated over the x-, y-, or z-axes. Simple 2D shape orientation was only rotated over the z-axis. (B) Scatter plot of the mean raw error for each individual for the simple 2D orientation raw error and complex 3D shape orientation tasks across the x- and y- axes of rotation. (C) Participants' mean raw error, (D) guess rate, and (E) precision comparison between the report of simple 2D and complex 3D object orientation across axis rotation. (F-H) Scatter plot of the mean raw error for each individual between the complex 3D orientation raw error across all axes of rotation. The trend lines represent the linear best fit for each condition. Error bars represents standard error.

Results

In this experiment, we investigated the properties of VSTM representations of complex 3D objects rotated over different 3D axes (x-, y-, and z-axes) and compared

them with a simple 2D line rotation. Here again, we used raw error as a measure of participant's performance. In addition, we applied the two-component mixture model (Zhang & Luck, 2008) to obtain the proportion of guesses separately from the precision of correct responses. Note that the manipulation over the z-axis for both the simple and complex shape is a direct replication of the set size 1 condition in Experiment 1.

Raw error. We first examined raw error as a measure of behavioural performance (see Figure 3C). To evaluate the memory performance for simple objects in comparison to complex objects, we computed frequentist and Bayesian paired t-tests. Significant differences were found across all three comparisons demonstrating a lower SD of responses for line orientations than complex objects rotated over the same axis (i.e., z-axis), $M_{diff} = 19.94^\circ$, $SD = 21.14^\circ$, $t(47) = 15.48$, $p < .001$, $d = 2.24$, $BF_{10} = 1.05e^{17}$, as well as over the x-axis, $M_{diff} = 30.46^\circ$, $SD = 31.33^\circ$, $t(47) = 25.29$, $p < .001$, $d = 3.65$, $BF_{10} = 5.37e^{25}$, and y-axis, $M_{diff} = 29.91^\circ$, $SD = 30.74^\circ$, $t(47) = 24.78$, $p < .001$, $d = 3.58$, $BF_{10} = 2.25e^{25}$. These results replicate the cost associated with complexity from Experiment 1.

To compare the raw error in reporting the orientation the complex 3D shapes over the x-, y-, and z-axes, one-way-within subject frequentist and Bayesian ANOVAs were conducted, revealing a significant difference between conditions, $F(1.73, 81.58) = 40.56$, $p < .001$, $\eta^2 = 0.463$, $BF_{10} = 4.38e^{10}$. Post-hoc comparison using frequentist t-tests with a Bonferonni correction and Bayesian t-test revealed significant differences between complex objects rotated over the z-axis and both the x-axis, $M_{diff} = 10.87^\circ$, $SD = 13.35^\circ$, $p < .001$, $BF_{10} = 3.21e^6$, and the y-axis, $M_{diff} = 9.97^\circ$, $SD = 13.35^\circ$, $p < .001$, $BF_{10} = 1.71e^6$. No significant difference between the 3D shape rotated over the x- and y-axes was found, $M_{diff} = 0.56^\circ$, $SE = 1.03^\circ$, $p > .999$, $BF_{10} = 0.18$.

In order to determine whether there is a relationship between one's ability to remember the simple 2D object orientation and 3D complex shapes across the z-axis (see results from Experiment 1 and Figure 1E for x-axis aggregated correlation) and the x- and y-axes (see Figure 3B), pairwise Pearson's correlations and Bayes correlation factors were computed on participant's mean raw error. Although the relationship between the raw error for simple 2D and complex 3D items over the x-axes shows a significant but

small correlation, $r = .356, n = 48, p = .013$, where 12.7% of the variance is accounted for, Bayesian factor shows that there is only anecdotal evidence for the alternative hypothesis over the null, $BF_{01} = 3.57$. There was no significant relationship between the 2D item and 3D shape rotated over the y-axis, $r = .267, n = 48, p = .067$, and a virtual absence of evidence for either the null or alternative hypotheses, $BF_{01} = 0.916$.

Turning to the inter-relationship between 3D rotations, significant correlations were found between the z-axis and both the x-axis (see Figure 2F), $r = .372, n = 48, p = .009$, and the y-axis (see Figure 2G), $r = .387, n = 48, p = .007$, and moderate evidence for the alternative hypothesis, respectively: $BF_{01} = 0.207$; $BF_{01} = 0.154$. A moderate correlation was found between the in the report of the orientation of complex shapes rotated across the x- and y-axes (see Figure H), $r = .671, n = 48, p < .001$, and Bayesian factor reveals very strong evidence towards the alternative hypothesis ($BF_{10} = 9.97e^4$). These results demonstrate that one's ability to remember the orientation of complex shapes over 3D axes are strongly interrelated, particularly when the object is affected by the same occlusion constraints (i.e. rotation over the x- and y-axes).

Mixture Model

Proportion of guesses. Next, we examined the effect of 3D rotation on the proportion of guesses (see Figure 2D). Frequentist and Bayesian t-test comparisons revealed a decreased proportion of guesses in reporting simple object orientation compared to complex objects rotated over the z-, x-, and y-axes, Z-axis: $M_{diff} = 6.3\%, SD = 7.8\%, t(47) = 7.66, p < .001, d = 1.11, BF_{10} = 1.35e^7$; X-axis: $M_{diff} = 19.4\%, SD = 21.0\%, t(47) = 12.73, p < .001, d = 1.84, BF_{10} = 7.77e^{13}$; Y-axis: $M_{diff} = 18.7\%, SD = 20.1\%, t(47) = 13.60, p < .001, d = 1.96, BF_{10} = 8.39e^{14}$. Here again, we have evidence that of a decrease in memory performance related to the complexity of the object memorized. Frequentist and Bayesian repeated measures ANOVA evaluating the proportion of guesses between 3D rotations for complex shape reveal significant differences, $F(1.85, 86.693) = 68.618, p < .001, \eta^2 = 0.593, BF_{10} = 1.34e^{16}$, where post-hoc comparisons reveal lower guess rate for the complex shape rotated over the z-axis compared to the x- and y- axes, X-axis: $M_{diff} = 13.2\%, SD = 15.8\%, t(47) = 9.30, p < .001, d = 1.34, BF_{10} = 2.72e^9$; Y-

1 axis: $M_{diff} = 12.4\%$, $SD = 14.9\%$, $t(47) = 14.31$, $p < .001$, $d = 1.43$, $BF_{10} =$
 2 $1.90e^{10}$, but not between the x- and y-axes, $M_{diff} = 0.70\%$, $SD = 10.4\%$, $t(47) =$
 3 0.68 , $p > .999$, $d = 0.10$, $BF_{10} = 0.195$.

4 **Target precision.** Finally, we evaluated the differences in response precision
 5 between the VSTM of simple object as it compares to complex object rotated over the
 6 three possible axes using frequentist and Bayesian t-test (see Figure E). Participants
 7 showed greater precisions reporting simple objects across all 3 rotations of the complex
 8 objects, Z-axis: $M_{diff} = 5.98^\circ$, $SD = 6.75^\circ$, $t(47) = 15.70$, $p < .001$, $d = 2.27$, $BF_{10} =$
 9 $1.84e^{17}$; X-axis: $M_{diff} = 10.11^\circ$, $SD = 11.27^\circ$, $t(47) = 14.08$, $p < .001$, $d =$
 10 2.03 , $BF_{10} = 2.99e^{15}$; Y-axis: $M_{diff} = 11.08^\circ$, $SD = 11.32^\circ$, $t(47) = 16.43$, $p <$
 11 $.001$, $d = 2.37$, $BF_{10} = 1.06e^{18}$. Here again, we reveal the same pattern exhibited by the
 12 previous measures, where a strong cost associated with complexity is present and
 13 decreases performance on the precision of the memorized item.

14 Repeated measures frequentist and Bayesian ANOVA revealed significant
 15 precision differences in reporting the orientation of the complex object across the three
 16 axes of rotations, $F(2.00, 93.78) = 33.38$, $p < .001$, $\eta^2 = 0.415$, $BF_{10} = 6.62e^8$. Post-
 17 hoc comparison using frequentist and Bayesian t-tests reveals greater precision for the
 18 complex shape rotated over the z-axis compared to the x- and y- axes, X-axis: $M_{diff} =$
 19 4.13° , $SD = 6.54^\circ$, $t(47) = 6.21$, $p < .001$, $d = .90$, $BF_{10} = 1.14e^5$; Y-axis: $M_{diff} =$
 20 5.10° , $SD = 5.69^\circ$, $t(47) = 7.55$, $p < .001$, $d = 1.09$, $BF_{10} = 9.27e^6$, but not between
 21 the x- and y-axes, $M_{diff} = 0.97^\circ$, $SD = 4.61^\circ$, $t(47) = 1.50$, $p = .425$, $d = 0.22$, $BF_{10} =$
 22 0.425 . The precision of the memorized items rotated over the x- and y-axes are greatly
 23 reduced in comparison to rotation over the z-axis. This pattern mirrors those of other two
 24 behavioural measures of raw error and Mixture Model guess rates.

25 Discussion

26 Experiment 2 takes advantage of the nature of the 3D objects to investigate the
 27 psychophysical properties short-term memory for orientation rotated over all three axes
 28 and compare them to the more commonly employed 2D line stimuli rotated over the z-
 29 axis only. Looking at the performance on the simple 2D line and complex 3D shape tasks
 30 when rotated over the z-axis, it appears that we successfully replicated the finding from

Experiment 1. Participants exhibited lower raw error when reporting the orientation of simple stimuli compared to the complex 3D shapes. Unlike Experiment 1, these results also consistently extended to the mixture model parameters of guesses and precision. Here again, these results indicate a cognitive cost associated with complex shapes when performing a short-term memory recall task.

Participants also exhibited a greater proportion of guesses and reduced precision when the complex 3D object was rotated over the x- and y-axes relative to the z-axis. A potential explanation for these results comes from the partial occlusion of the object, which may render the task of recognizing the 3D object as a whole object more difficult. A shape rotated over the z-axis will present all of its relevant features regardless of its orientation, whereas objects rotated over the x- or y-axes will have a significant portion of features occluded by the most forward features. Thus, it is difficult to encode and report accurately the orientation of an object when one can rely on only a small portion of its key features, and when those features change as a function of the recall angle. It is interesting to note that, in terms of raw error and precision, there is a greater difference between reporting simple line orientations compared to 3D objects as opposed to the difference between the 3D shapes rotated over the z-axis compared to the x- and y-axes.

The pattern of correlations found across conditions in Experiment 2, along with the psychophysical similarities, highlights the involvement of shared processes for VSTM across the simple 2D and complex 3D shapes. Despite this similarity, there may be important differences between remembering even 3D shapes, as revealed by the decreased performance for memory around the x- and y-axes. Marr and Nishihara (1978) proposed a model of visual processing that begins with a primal sketch, which reflects a 2D representation based on the essential features of an object, followed by a 2.5D sketch that acknowledge depth relations between the various 2D features, and finally, a 3D model that presents a continuous spatial relationship among the feature of the object. In this experiment, our complex shapes rotated over the z-axis may qualify as a 2.5D objects, as the occlusion caused by the object's feature remains static through the rotation around the axis; inferring the true 3D spatial distances of the object would not confer any advantage to the task performance. In contrast, complex objects rotated over the x- and y-axes need

1 to be understood as 3D objects in order to identify the appropriate orientation. The
2 strong correlation between raw errors in the rotation of complex objects over the x-
3 and y-axes suggests a considerable overlap between the underlying mechanisms
4 relative to the weaker relationship with the simple line or 3D shapes rotated over
5 the z-axis. However, the finding that the effect of shape complexity has a greater effect
6 on VSTM performance than partial occlusion suggests that, while the axis of orientation
7 may fundamentally affect the underlying VSTM abilities, the nature of the stimuli
8 remains of fundamental importance to VSTM performance, even when all the features are
9 visible.

10 **General Discussion**

11 The primary aim of this study was to evaluate the generalizability of VSTM from
12 simple features (i.e., orientations) to more complex, 3-dimensional objects. As such we
13 evaluated the accuracy of reporting 2D line and 3D objects in a continuous-response
14 recall paradigm, manipulating set size in Experiment 1 and the axis of rotation in
15 Experiment 2. The results of both experiments demonstrate a general cost on all
16 psychophysical measures (i.e. raw error, proportion of guesses, and precision) associated
17 with the memory for complex 3D objects compared to simple 2D objects, with the
18 exception of precision in Experiment 1 (see the Experiment 1 – Discussion for a
19 description of why this result should be interpreted with caution). Despite some evidence
20 demonstrating that complexity does not significantly impact the psychophysical
21 properties of VSTM representation (e.g., Awh, Barton, & Vogel, 2007; Luck & Vogel,
22 1997), this finding is in line with previous studies that have observed behavioural costs
23 associated with remembered complex compared to simple stimuli (Alvarez & Cavanagh,
24 2004; Delvenne & Bruyer, 2004; Rademaker et al., 2018; Wheeler & Treisman, 2002)
25 and modulated neural activity associated with remembered complex compared to simple
26 stimuli (Luria et al., 2010; Wilson et al., 2012). We also observed in Experiment 2 that
27 memory for 3D shapes was not consistent across all axes of rotation, with all measures of
28 accuracy indicating better performance around the z-axis than over the x- and y-axes. To
29 our knowledge, these results provide the first demonstration of the psychophysical
30 properties of VSTM for 3D shapes in a recall task, as well as demonstrating the
31 additional challenges faced for remembering 3D shapes in space. These results add to a

growing literature indicating that VSTM is not a unitary phenomenon affected only by the number of stimuli that have to be stored. Instead, VSTM is affected by a myriad of perceptual and cognitive factors that includes the support of sensory-specific brain regions, strategy-dependent mechanisms and 3D-related processes (each of which are discussed below).

Although the correlation between raw error when reporting simple and complex objects is small given that both tasks require participants to remember the same feature (i.e., orientation) of the stimulus presented, the Bayes Factor comments on the strong likelihood in favor of the relationship. The relatively low shared variance accounted for in the relationship between simple and complex objects still remains surprising, which suggests the involvement of some partially independent processes. Because our recall tasks only differ in the type of stimuli presented, the different processes at play here are likely related to the nature of the stimulus. According to the sensory recruitment hypothesis, VSTM maintenance is sustained through the continuous recruitment of the same cortical regions that were initially required for the encoding of the information (Ester, Serences, & Awh, 2009; Postle, 2006; Serences, 2016; Serences, Ester, Vogel, & Awh, 2009). For instance, Druzgal & D'Esposito (2001) have demonstrated the involvement of the fusiform face area (FFA) during the maintenance of face stimuli in a working memory task. Similarly, studies have demonstrated that decoding fMRI BOLD activity recorded in V1 can reliably identify the orientation of grating patterns (Albers, Kok, Toni, Dijkerman, & de Lange, 2013; Harrison & Tong, 2009), and those remembering the direction of motion show stimulus-specific activity in area MT (Emrich, Riggall, Larocque, & Postle, 2013; Riggall & Postle, 2012). Consequently, it is possible that committing a complex 3D-shapes to memory may recruit more anterior regions of the ventral visual stream, whereas simple lines mainly rely largely on the orientation-tuned neurons in primary visual cortex. Moreover, studies have shown that 3D shapes are processed in areas of the dorsal visual stream (Króliczak, McAdam, Quinlan, & Culham, 2008; Theys, Romero, van Loon, & Janssen, 2015). Thus, the low variance accounted for between simple and complex objects found in this study may reflect the fact that memory for 3D shapes requires the recruitment of large networks of visual regions not required for simple 2D line orientations. This may have important implications for models of

1 VSTM, as manipulating stimulus complexity may necessitate the recruitment of higher
2 visual areas, despite sharing a common, relevant feature (i.e., orientation).

3 The observed behavioural differences between simple and complex objects may
4 also exist because of differences in cognitive strategies to complete the tasks. Although
5 VSTM experiments typically do not consider participants' strategies, several studies have
6 found significant effects strategy on performance and neural measures. For example,
7 using principal component analysis, Miller, Donovan, Bennett, Aminoff, & Mayer (2012)
8 provided evidence that individual cognitive style and encoding strategy accounted for a
9 significant portion of the variance in the similarity of BOLD activity between
10 participants. Similarly, instructing participants to use specific strategies to perform
11 working memory tasks can improve the behavioural performance of lower IQ individual
12 (Linke, Vicente-Grabovetsky, Mitchell, & Cusack, 2011) and change memory encoding
13 (Vicente-Grabovetsky, Carlin, & Cusack, 2014). Studies of mental imagery have also
14 provided evidence suggesting between-subject differences in the preference for spatial- or
15 object-based visualizing styles (Kozhevnikov, Hegarty, & Mayer, 2002; Kozhevnikov,
16 Kosslyn, & Shephard, 2005). Thus, it is possible that participants may not only engage in
17 a different strategy based on the type of task (see Pearson & Keogh (2019) for more
18 details) but also based on the nature of the stimulus presented.

19 Although some psychophysical properties of simple objects do transfer to more
20 complex stimuli, our results suggest that other processes are involved not only when the
21 stimulus is in 3D but also when they are rotated over different axes. While the VSTM
22 literature tends to draw conclusions from very simple and tightly controlled stimuli (e.g.,
23 coloured squares, line orientation, etc.), it often makes the implicit assumption that these
24 factors are transferable to other stimuli. Along with our results, recent studies that varied
25 stimulus presentation in a ways that is uncommon in the VSTM literature demonstrated
26 the contribution of processes that are not yet fully understood. For example, Chunharas et
27 al. (2019) recently demonstrated that memory for colors is improved when stimuli were
28 presented in different 3D planes. Aagten-Murphy and Bays (2019) also recently showed
29 that spatial VSTM has separate egocentric and allocentric frames of reference. Brady,
30 Shafer-Skelton, & Alvarez (2017) showed that scenes are more recognizable using global
31 texture cues rather than from the objects found in the scene. These studies are a few

1 examples taken from a growing body of literature suggesting that a multitude of factors
2 can affect VSTM. Generalizing findings derived from overly simplified stimuli therefore
3 increases the risk of overlooking important sources of variance that may be more
4 ecologically relevant than those already identified. Consequently, given the similarities in
5 performance between 2D lines and 3D shapes observed here, future studies may benefit
6 to use more complex 3D shapes to better understand the complete nature of VSTM.
7

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