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Precision in spatial working memory examined with mouse pointing

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A R T I C L E I N F O

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A B S T R A C T

The capacity of visuospatial working memory (VSWM) is limited. However, there is continued debate surrounding the nature of this capacity limitation. The resource model (Bays et al., 2009) proposes that VSWM capacity is limited by the precision with which visuospatial features can be retained. In one of the few studies of spatial working memory, Schneegans and Bays (2016) report that memory guided pointing responses show a monotonic decrease in precision as set size increases, consistent with resource models. Here we report two conceptual replications of this study that use mouse responses rather than pointing responses. Overall results are consistent with the resource model, as there was an exponential increase in localisation error and monotonic increases in the probability of misbinding and guessing with increases in set size. However, an unexpected result of Experiment One was that, unlike Schneegans and Bays (2016), imprecision did not increase between set sizes of 2 and 8. Experiment Two replicated this effect and ruled out the possibility that the invariance of imprecision at set sizes greater than 2 was a product of oculomotor strategies during recall. We speculate that differences in imprecision are related to additional visuomotor transformations required for memory-guided mouse localisation compared to memory-guided manual pointing localisation. These data demonstrate the importance of considering the nature of the response modality when interpreting VSWM data.

1. Introduction

Although we can perceive a rich visual world, we cannot retain all the information presented to us at any given time (Adam et al., 2017; Luck & Vogel, 2013; Ma et al., 2014). Visuospatial working memory (VSWM) is the cognitive system that allows us to temporarily maintain and manipulate limited amounts of visual and spatial information about objects (Baddeley, 2000). There is continued debate surrounding the nature of the capacity limitation in VSWM. One influential proposal is that there is a flexible limit on VSWM capacity, where the limit is based on the fidelity with which items can be retained in VSWM (Bays et al., 2009; Zokaei et al., 2011). This resource model of VSWM draws primarily on studies that utilise the continuous report task (Wilken & Ma, 2004), which requires participants to reproduce a visual feature, such as colour or orientation of a probe along a continuous dimension, after a short delay. The distribution of recall error can therefore be examined to probe the sources of recall error and provide an insight into the precision with which representations are encoded and stored, providing a more sensitive measure of VSWM compared to span methods (Zokaei et al., 2015).

Using this approach, Bays et al. (2009) showed that precision significantly decreased when set size increased, even with an increase from one to two items. The decrease in precision was accompanied by increasing misbinding errors, where a feature of a non-probed item was reported, as set size increased, even up to six items. This finding indicates that all visual features in an array are encoded into VSWM, but with increasing noise as more features need to be retained. Bays et al. (2009) argued that when participants are retrieving items from VSWM, all visual and spatial features of each item must be correctly bound together. As a consequence, when participants incorrectly respond on a given trial, they may be responding with the feature of another presented item from the original array (misbinding), or they may be responding at random (guessing). In line with the resource model proposal that all items are encoded into VSWM, when misbinding errors are accounted for, the proportion of variance in the data explained by guessing significantly decreases (Bays et al., 2009).

This finding has been replicated across a variety of non-spatial (visual) features, including colour, orientation, and motion direction (Gorgoraptis et al., 2011; Zokaei et al., 2014, 2011). However, fewer studies have modelled the precision and error in spatial working memory. Given the well-established dissociations between memory for visual features and spatial locations in VSWM (Darling et al., 2006; Darling

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et al., 2009), it is likely that the pattern of response errors in memory for spatial locations might differ from those observed in memory for visual features.

Pertzov et al. (2012) modified the continuous report task to probe memory for locations, by asking participants to relocate objects to their original locations at test. They found that, as set size increased from one to five objects, localisation error increased. Moreover, the probability of committing misbinding errors increased with set size. This finding indicates that the representation of spatial locations within VSWM can be characterised by the resource model. However, the use of naturalistic objects in this study is problematic due to their complexity, which may have reduced precision overall (Chen et al., 2017).

Schneegans and Bays (2016) addressed these criticisms by presenting coloured dots to participants in a spatial continuous report task. As set size increased from one to eight items, they found a monotonic increase in localisation error with a corresponding increase in the prevalence of misbinding errors, indicating that all items had been encoded into VSWM. There was also a monotonic increase in the imprecision of memory representations as more items were to be retained, with a statistically significant increase between four and eight items. However, only a limited number of set sizes were examined (1, 2, 4, and 8 items), so the claim of a linear increase in localisation error with increases in set size should be treated with caution. As a result of using such a limited number of set sizes, the data may have lacked the granularity to detect subtle differences in the pattern of recall errors that may have occurred between encoding and maintenance of four and eight items.

While the method used by Schneegans and Bays (2016) may have provided an accurate measurement of recall error, it is not an accessible measurement of VSWM. Indeed, many studies ask participants to use button or mouse responses during recall in VSWM tasks (e.g. Bays et al., 2009 used a computer mouse). Using a mouse response has some advantages compared to using the finger-pointing set-up used by Schneegans and Bays (2016). Firstly, a large number of participants can be tested, for example online, because it does not rely on specialist touchscreen equipment. Secondly, using a mouse cursor standardises the size of the target that must be localized at recall. Thirdly, mouse responses are not necessarily constrained by the same kinematic limitations as the ballistic pointing response used by Schneegans and Bays (2016), for example systematic hypometria (Becker, 1972) so may afford more precise localisation. However, using a mouse response also requires spatial transformations that are not required for pointing actions, and it is unclear if or how this affects performance on spatial working memory tasks. The current experiments therefore sought to examine whether and how memory for spatial locations might be affected by using a mouse localisation response.

2. Experiment one

2.1. Method

2.1.1. Participants

We carried out an *a priori* power analysis using G*Power v3.1.9.7 (Faul et al., 2009) to determine the required minimum sample size. Based on Schneegans and Bays (2016), we required a sample of at least two participants to detect a large effect of set size on response error ($\eta_p^2 = 0.83$) with 95% power and an alpha level of 0.05. We recruited 14 volunteers ($M_{\text{age}} = 20.43$ years, $SD_{\text{age}} = 1.34$, 9 females, 4 males, 1 non-binary, 13 right-handed) from the Department of Psychology participant pool. Undergraduate participants who were enrolled on the Psychology course at Durham University were credited with participant pool credit for their time. The study received ethical approval from Durham University Psychology Department Research Ethics Committee (reference: PSYCH-2019–10-28 T15:23:58-lckd86).

2.1.2. Design

We used a within-subjects design. The independent variable was set size, with eight levels (set sizes 1 to 8). The dependent variable was localisation error, measured by the Euclidean distance between the participant responses and the original location of the probe item. Imprecision, probability of reporting a target, probability of misbinding, and the probability of guessing, which were obtained from the best fitting mixture model (Bays et al., 2009), were additional dependent variables.

Participants completed one practice block comprising eight trials, one of each set size, to familiarise themselves with the task. The practice block was identical to the experimental blocks, with the exception that participants were shown their own response as well as the original location of the probe stimulus after submitting their response. They then completed 400 trials, randomised across 10 blocks, with each set size being tested 50 times.

2.1.3. ***Stimuli*** and ***Apparatus***

The task was programmed using Matlab R2019a, using the psychophysics toolbox (Kleiner et al., 2007), and was based on Schneegans and Bays (2016). The stimuli consisted of arrays comprising between one and eight coloured dots (diameter of each dot = 1° VA) and a fixation cross (0.76° VA x 0.76° VA) positioned at the centre of the screen. The fixation cross was present only at the beginning of each trial and was not present during encoding, maintenance, recall. The colours of each dot were chosen without repetition from a bank of eight discriminable colours: red, orange, yellow, green, cyan, blue, magenta, and purple. The visual mask comprised 800 coloured dots, like those presented at encoding, filling the annular space five to ten degrees of visual angle around central fixation. Participants' gaze was monitored using a tower-mounted EyeLink 1000 eye tracker (SR Research). Stimuli were presented on a 20-inch CRT screen with a refresh rate of 85 Hz. Participants sat 60 cm from the computer screen, with the centre of the screen at eye level.

2.2. Procedure

Participants were instructed to maintain fixation on the centre of the screen throughout each trial. Trials began with presentation of a fixation cross at the centre of the screen for one second followed by a blank screen for 0.5 s. The stimulus array, comprising between one and eight coloured dots, was then presented for two seconds. The location of each dot was randomly chosen within the annular region between five and ten degrees of visual angle around central fixation. Each dot was positioned at least 1.5° of visual angle from other dots to ensure no overlap in their locations. After presentation of the array, the visual mask was presented for 0.1 s. A blank screen was then shown for 0.9 s. At test, one of the stimuli from the array was randomly chosen and presented in the centre of the screen. Participants were required to move the mouse to click the location on screen where it first appeared. Participants could respond with any location on screen as they were unaware that the stimulus presentation area was restricted. There was no time limit for responding. A one second blank screen followed the response period, before the beginning of the next trial. Participants were permitted to take a self-paced break between blocks. An example trial is shown in Fig. 1.

3. Results

All inferential tests were carried out in R (R Core Team, 2019), using the rstatix package (Kassambara, 2019). Greenhouse-Geisser correction was applied if the assumption of sphericity was violated. Trials in which average saccade amplitude exceeded two degrees of visual angle during encoding and maintenance were removed from analysis to control for eye movements. This resulted in the full datasets of two participants being excluded due to missing data. Of the remaining 12 participants,

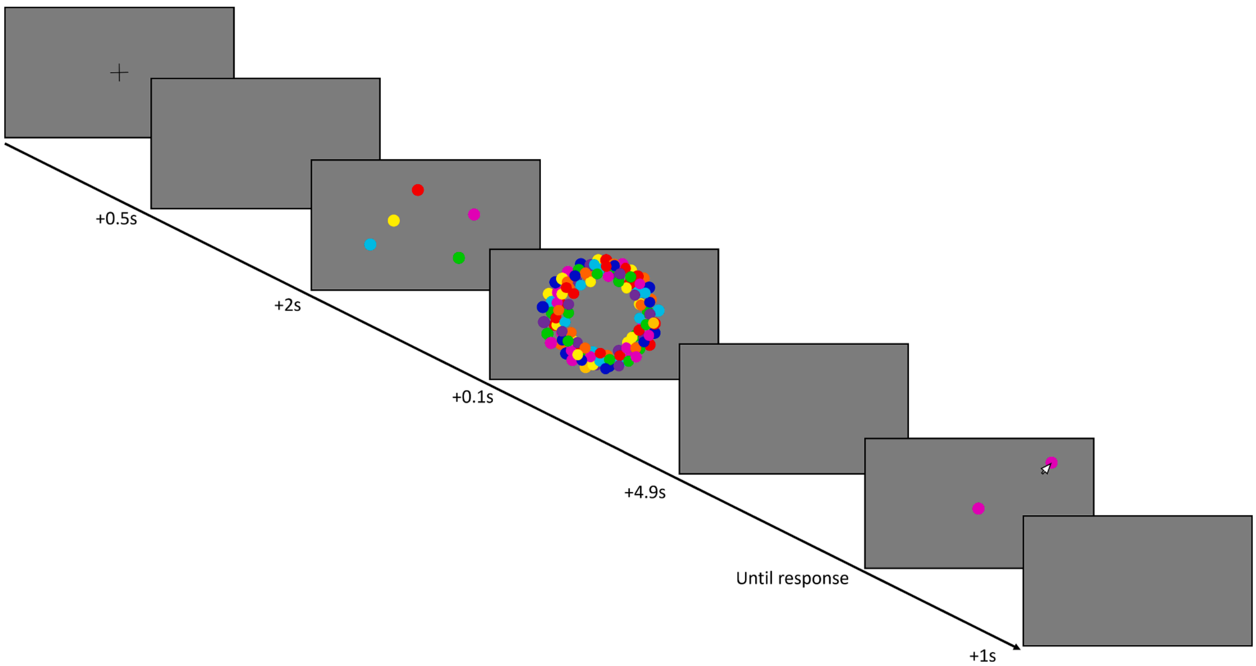

Fig. 1. An example trial in Experiment One. Participants were shown an array of between one and eight dots. After a short delay, they were asked to click on screen where one of those dots first appeared.

14.56% of trials were excluded due to eye movements.

Localisation error, measured by the Euclidean distance in pixels between the probed location and the participant's response on screen, was first examined to gain an overview of the pattern of response error. We then fit a series of mixture models to examine the sources of recall error and to gain a greater insight into the ways in which recall error

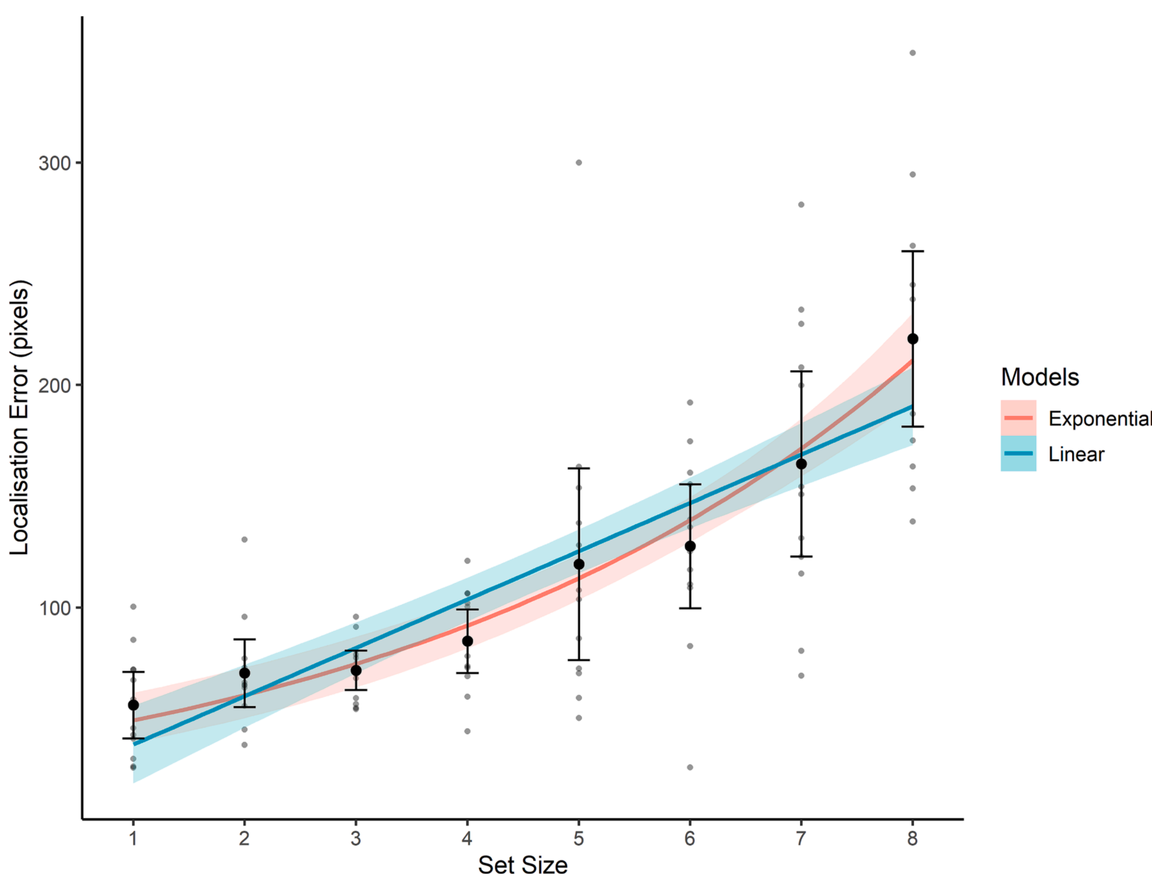

Fig. 2. Localisation error as a function of set size for each participant, with the best-fitting linear and exponential models plotted. The shaded regions represent 95% confidence intervals. Mean values are shown in black, with the error bars representing 95% confidence intervals.

varied with changes in set size. Localisation error can be considered a proxy for precision, but it does not assume the distribution from which the response is drawn.

3.1. Localisation error

Mean localisation error is displayed in Fig. 2. There is a clear increase in localisation error as set size increases, as confirmed with one-way repeated-measures ANOVA; $F(3.45,\ 37.97) = 24.18$, $p < 0.001$, $\eta_p^2 = 0.69$. Bonferroni-Holm corrected pairwise comparisons between adjacent set sizes revealed no significant differences; $p \geq 0.069$.

Simple linear regression was then carried out to examine whether set size predicts localisation error (Fig. 2). Set size was a significant predictor of localisation error; $m = 21.7$, $SE = 2.09$, $p < 0.001$. However, the constant was not significant in this model; $c = 16.86$, $SE = 10.58$, $p = 0.114$. Additionally, this model accounted for only 53% of variance in the data; $R^2_{adjusted} = 0.53$, $F(1, 94) = 107.32$, $p < 0.001$. Examination of the data (Fig. 2) suggested that an exponential model might provide a better fit to the data. An exponential model in the form $localisation\ error = a{*}exp(b{*}set\ size)$ was fit to the data. Both the constant [$a = 40.08$, $SE = 5.34$] and set size [$b = 0.21$, $SE = 0.02$] were significant; $p < 0.001$. Akaike Information Criterion values corrected for sample size (AICc) were calculated for both models to assess their relative fits to the data. Comparison of AICc values, when calculated for the models on the whole dataset (See S1 for individual level data), revealed that the exponential model provided a better fit to the data compared to the linear model; $\Delta AICc_{Total} = 9.91$.

3.2. Mixture *modelling*

3.2.1. Model Comparison

Mixture modelling was then carried out using MemToolbox2D (Grogan et al., 2020; Suchow et al., 2013) to examine which model best fit the response data for each participant. We firstly compared the fit of the two-component mixture model (Zhang & Luck, 2008), which comprises a normal and uniform distribution to that of Bays et al. (2009), which comprises a normal distribution, misbinding errors and a uniform distribution. We also compared these models to a model that comprised only a normal distribution centred on the target location (Fig. 3). The best fitting model across all participants, with the lowest AICc, was one that included a normal distribution centred on the target location, misbinding errors, and guesses corrected by assuming that responses were sampled from the annulus within which stimuli could appear, although this was only a marginally better fitting model compared to that which assumed no response sampling and was no different to the model without response sampling in some participants (Bays et al., 2009); *normal distribution only:* $M\ \Delta AIC_c = 1053.57$; *normal distribution with guessing:* $M\ \Delta AIC_c = 717.83$; *normal distribution with guessing, misbinding, and no response sampling:* $M\ \Delta AIC_c = 6.04$.

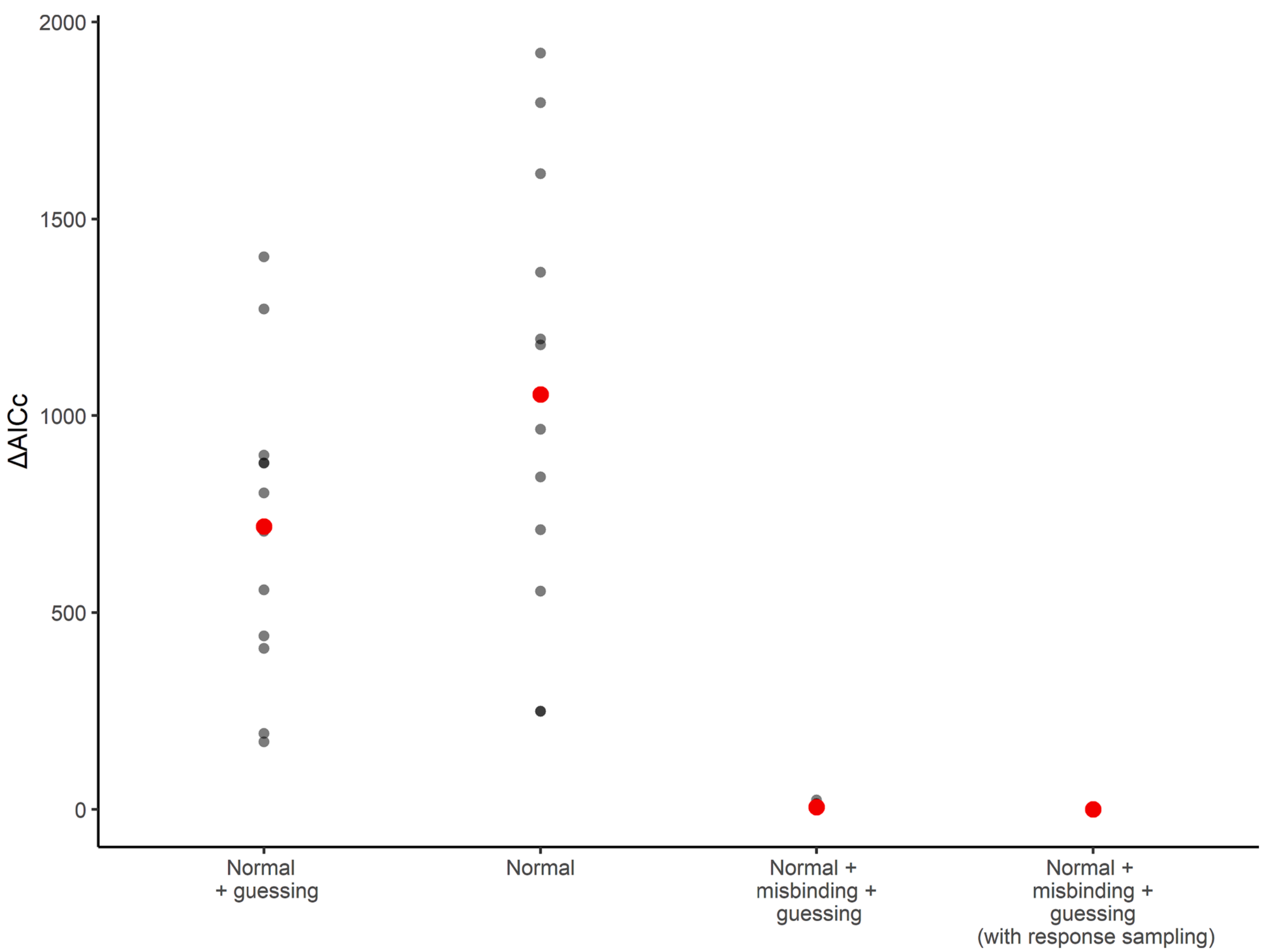

Fig. 3. Difference in AICc scores of each mixture model for each participant compared to best fitting model. Mean difference is highlighted in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2.2. Sources of recall error

We fit the best fitting model, which included response sampling, to each set size condition and analysed how the sources of error changed across set sizes. Analysis of imprecision (Fig. 4A) revealed a significant main effect of set size; $F(2.59, 28.48) = 3.58$, $p = 0.031$, $\eta_p^2 = 0.24$. Bonferroni-Holm corrected pairwise comparisons showed a significant increase in imprecision when set size increased from one item (M = 41.32, SD = 13.68) to two items (M = 55.2, SD = 14.93); $p = 0.016$. No other differences were significant; $p \geq 0.768$.

For the probability of reporting the target (Fig. 4B), there was a main effect of set size; $F(2.45, 26.93) = 28.75$, $p < 0.001$, $\eta_p^2 = 0.72$. Bonferroni-Holm corrected pairwise comparisons indicated that participants were significantly more likely to report the target location at set size 3 (M = 0.98, SD = 0.04) than at set size 4 (M = 0.92, SD = 0.08). The differences between set size 4 and set size 5 (M = 0.78, SD = 0.18), and set size 7 (M = 0.68, SD = 0.16) and set size 8 (M = 0.54, SD = 0.23) were also significant; $p \leq 0.045$. No other comparisons were significant; $p \geq 0.345$.

For the probability of misbinding (Fig. 4C), a significant main effect of set size was observed; $F(3.04, 33.45) = 10.76$, $p < 0.001$, $\eta_p^2 = 0.5$. Bonferroni-Holm corrected pairwise comparisons showed that participants were significantly more likely to report a non-target at set size 4 (M = 0.09, SD = 0.08) compared to set size 3 (M = 0.02, SD = 0.04); p = 0.031. No other comparisons were significant; $p \geq 0.076$.

Finally, for the probability of guessing (Fig. 4D), there was a significant main effect of set size; $F(7, 77) = 8.92$, $p < 0.001$, $\eta_p^2 = 0.45$. However, Bonferroni-Holm corrected pairwise comparisons revealed no significant differences between set sizes; $p \geq 0.061$.

4. Discussion

This experiment showed that localisation error increased exponentially as set size increased from one to eight items. Mixture modelling (Bays et al., 2009; Grogan et al., 2020) showed that the best fitting model to our response data was one that includes misbinding errors (Bays et al., 2009) compared to a model that only includes a normal distribution and guessing (Zhang & Luck, 2008). When we examined the effects of set size on the parameters of this model, the probability of reporting the target location decreased with set size, accompanied by increases in misbinding and guessing, indicating that items were encoded into VSWM, but with increasing noise as set size increased. Imprecision significantly increased between set size 1 and 2, but was stable at larger set sizes. These data differ from Schneegans and Bays (2016) in two ways. Firstly, we found that localisation error changed rapidly at set sizes larger than four items, with the relationship between set size and localisation error being better characterised by an exponential model compared to a linear model [*linear model*: $R^2_{adjusted} = 0.53$, AICc = 1016; *exponential model*: AICc = 1006.09]. Secondly, although we observed a monotonic increase in localisation error with set size, reflecting the fact that the absolute distance between the probed location and response location increased as set size increased, there were no significant changes in imprecision after set size 2. In contrast, Schneegans and Bays (2016) reported a monotonic increase in both error and imprecision, which was largest between set size 4 and set size 8. On first inspection it is tempting to attribute the contrary results to difference in response mode (mouse clicks vs manual pointing). However, unlike Schneegans and Bays (2016), fixation was not enforced during the recall phase during Experiment One. To examine whether saccadic behaviour during recall was responsible for the unexpected pattern of imprecision we

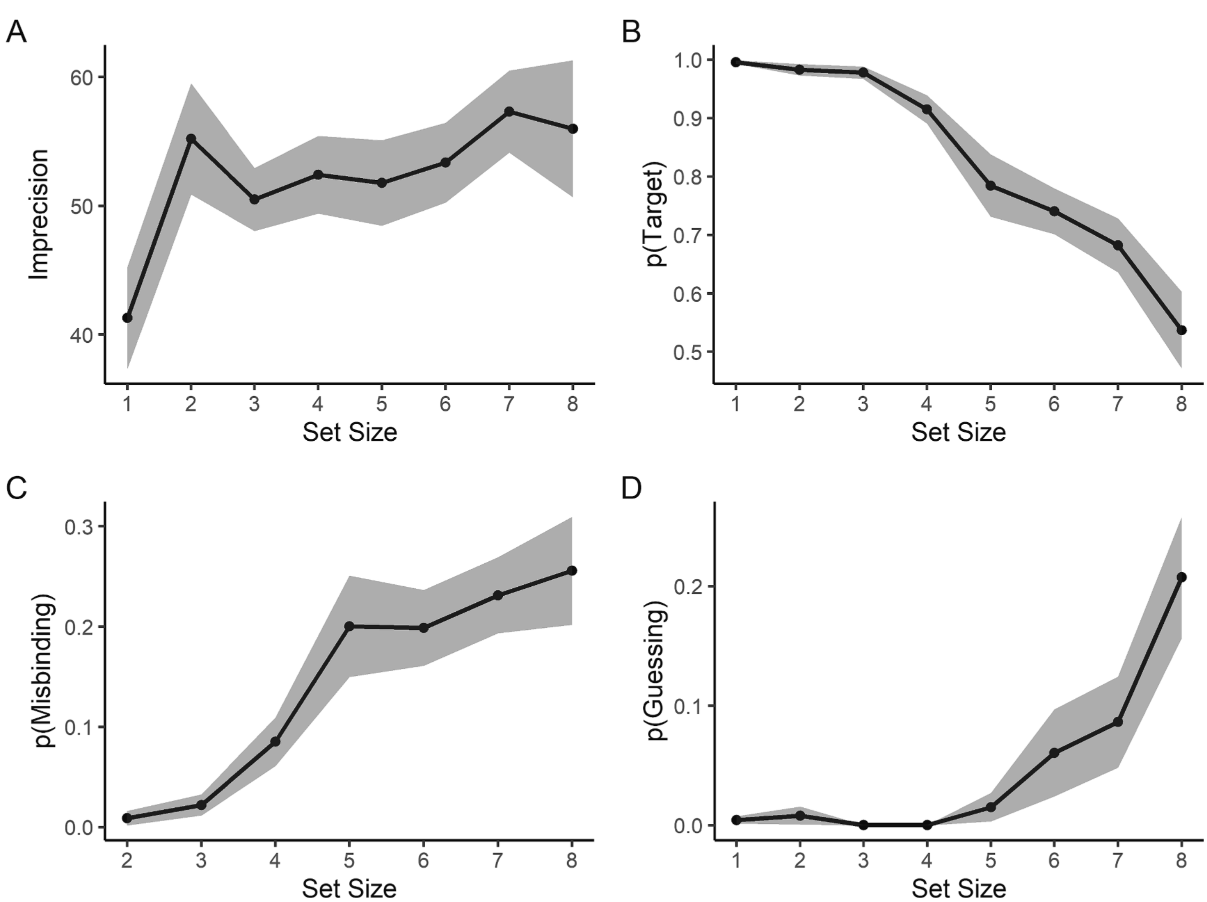

Fig. 4. Mean imprecision (a), mean probability of reporting the target location (b), mean probability of reporting a non-target (misbinding; c), and mean probability of guessing (d) as a function of set size. Shaded regions represent SEM.

carried out a second experiment in which fixation was enforced throughout encoding, maintenance, and retrieval.

5. Experiment two

5.1. Method

5.1.1. Participants

We carried out an *a priori* power analysis using G*Power v3.1.9.7 (Faul et al., 2009) to determine the required minimum sample size. Based on Experiment One, we required a sample of at least six participants to detect a medium effect of set size on imprecision ($\eta_p^2 = 0.24$) with 95% power and an alpha level of 0.05. We recruited 13 volunteers ($M_{age} = 24.15$ years, $SD_{age} = 8.92$, 11 females, 2 males, 13 right-handed) from the Department of Psychology participant pool. Undergraduate participants who were enrolled on the Psychology course at Durham University were credited with participant pool credit for their time. The study received ethical approval from Durham University Psychology Department Research Ethics Committee (reference: PSYCH-2019–10-28 T15:23:58-lckd86).

5.1.2. Design

Design matched Experiment One.

5.1.3. Stimuli and Apparatus

Stimuli were as described in Experiment One.

5.2. Procedure

Procedure matched Experiment One, with that additional constraint that fixation was enforced during recall.

6. Results

Trials in which average saccade amplitude exceeded two degrees of visual angle during the entire trial (encoding, maintenance, and recall) were removed from analysis to control for eye movements. This resulted in the full datasets of three participants being excluded due to missing data. Of the remaining 10 participants, 27.23% of trials were excluded due to eye movements.

6.1. Localisation error

Mean localisation error is displayed in Fig. 5. One-way repeated-measures ANOVA confirmed a main effect of set size; $F(2.05, 18.45) = 23.91$, $p < 0.001$, $\eta_p^2 = 0.73$. Bonferroni-Holm corrected pairwise comparisons between adjacent set sizes revealed a significant difference between set size 6 ($M = 106.79$, $SD = 28.99$) and set size 7 ($M = 147.88$, $SD = 36.74$); $p = 0.023$. However, no other differences were significant; $p \geq 0.198$.

Simple linear regression was then carried out to examine whether set size predicts localisation error (Fig. 5). Both set size ($m = 16.73$, $SE = 1.58$, $p < 0.001$) and the constant ($c = 23.2$, $SE = 7.98$, $p = 0.005$) were significant in this model. However, this model accounted for only 58 % of variance in the data; $R^2_{adjusted} = 0.58$, $F(1, 78) = 112.09$, $p < 0.001$. An exponential model in the form *localisation error* = *a***exp*(*b***set size*)

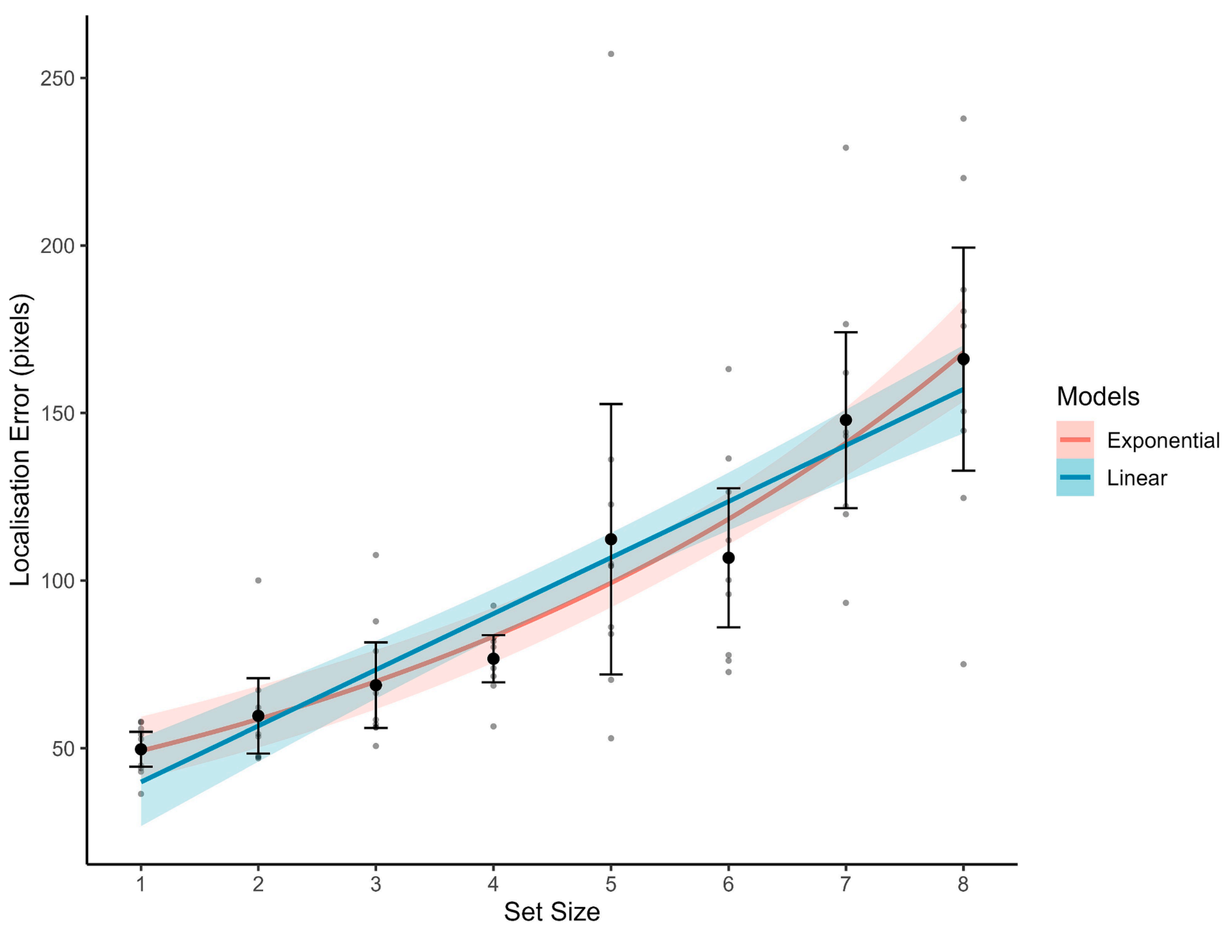

Fig. 5. Localisation error as a function of set size for each participant, with the best-fitting linear and exponential models plotted. The shaded regions represent 95% confidence intervals. Mean values are shown in black, with the error bars representing 95% confidence intervals.

was fit to the data. Both the constant [$a = 41.32$, $SE = 4.64$] and set size [$b = 0.18$, $SE = 0.02$] were significant; $p < 0.001$. Akaike Information Criterion values corrected for sample size (AICc) were calculated for both models to assess their relative fits to the data. Comparison of AICc values, when calculated for the models on the whole dataset (See S3 for individual level data), revealed that the exponential model provided a better fit to the data compared to the linear model; $\Delta AICc_{Total} = 3.56$.

6.2. *Mixture modelling*

6.2.1. *Model Comparison*

Mixture modelling was then carried out using MemToolbox2D (Grogan et al., 2020; Suchow et al., 2013) to examine which model best fit the response data for each participant. The best fitting model across all participants, with the lowest AICc, was one that included a normal distribution centred on the target location, misbinding errors, and guesses corrected by assuming that responses were sampled from the annulus within which stimuli could appear (Fig. 6), although this was only a marginally better fitting model compared to that which assumed no response sampling and was no different to the model without response sampling in some participants (Bays et al., 2009); *normal distribution only: M* $\Delta AIC_c = 1352.11$; *normal distribution with guessing: M* $\Delta AIC_c = 927.09$; *normal distribution with guessing, misbinding, and no response sampling: M* $\Delta AIC_c = 13.59$.

6.2.2. *Sources of recall error*

We fit the best fitting model, which included response sampling, to each set size condition and analysed how the sources of error changed across set sizes. Analysis of imprecision (Fig. 7A) revealed a significant main effect of set size; $F(7, 63) = 2.86$, $p = 0.012$, $\eta_p^2 = 0.24$. Bonferroni-Holm corrected pairwise comparisons showed no significant differences between adjacent set sizes; $p \geq 0.231$.

For the probability of reporting the target (Fig. 7B), there was a main effect of set size; $F(1.99, 17.93) = 24.4$, $p < 0.001$, $\eta_p^2 = 0.73$. Bonferroni-Holm corrected pairwise comparisons indicated that participants were significantly more likely to report the target location at set size 6 ($M = 0.79$, $SD = 0.13$) than at set size 7 ($M = 0.68$, $SD = 0.14$); $p = 0.007$. No other comparisons were significant; $p \geq 0.159$.

For the probability of misbinding (Fig. 7C), a significant main effect of set size was observed; $F(2.47, 22.21) = 6.24$, $p = 0.005$, $\eta_p^2 = 0.41$. Bonferroni-Holm corrected pairwise comparisons showed no significant differences between adjacent set sizes; $p \geq 0.256$.

Finally, for the probability of guessing (Fig. 7D), there was a significant main effect of set size; $F(1.34, 12.05) = 5.25$, $p = 0.033$, $\eta_p^2 = 0.37$. However, Bonferroni-Holm corrected pairwise comparisons revealed no significant differences between set sizes; $p \geq 0.416$.

6.2.3. *Comparison* ***of Experiment one and Experiment two***

Imprecision between Experiments One and Two was then compared (Fig. 8). The effect of set size was significant; $F(3.33, 66.62) = 6.03$, $p < 0.001$, $\eta_p^2 = 0.23$. Neither the main effect of experiment [$F(1, 20) = 0.66$, $p = 0.428$, $\eta_p^2 = 0.03$] nor the interaction between set size and experiment [$F(3.33, 66.62) = 0.31$, $p = 0.835$, $\eta_p^2 = 0.01$] were significant.

Bonferroni-Holm pairwise comparisons revealed a significant increase in imprecision between set size 1 ($M = 40.47$, $SD = 10.65$) and set size 2 ($M = 51.74$, $SD = 13.8$); $p = 0.001$. No other differences were

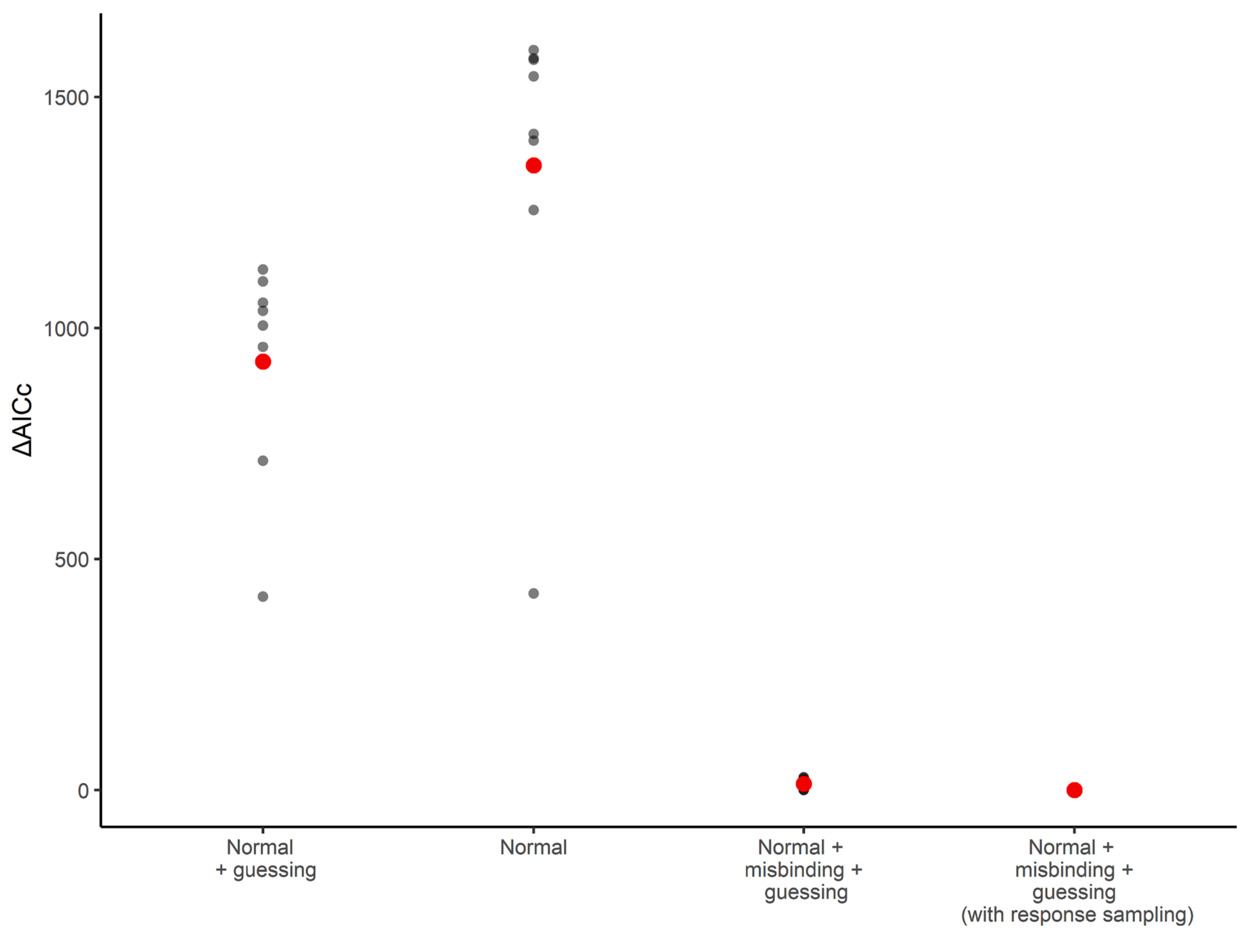

Fig. 6. Difference in AICc scores of each mixture model for each participant compared to best fitting model. Mean difference is highlighted in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

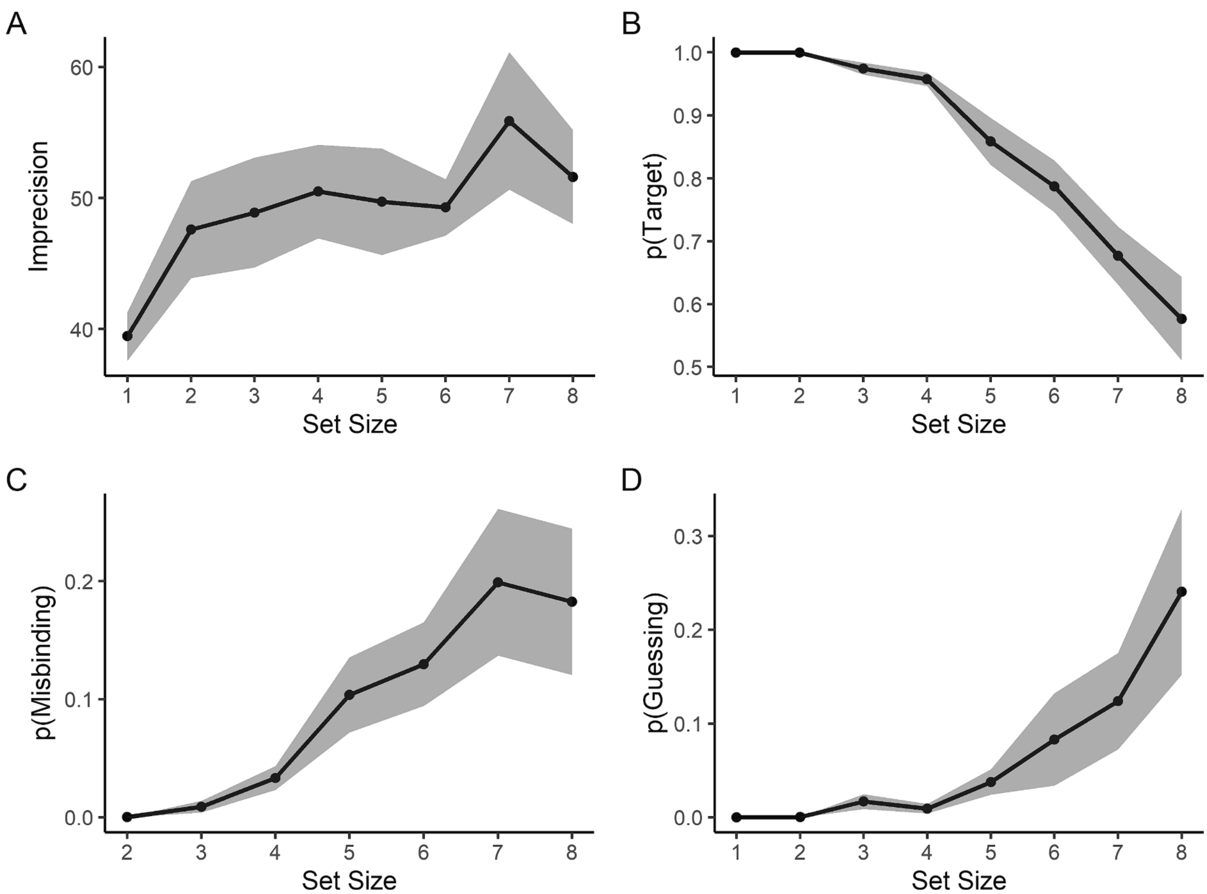

Fig. 7. Mean imprecision (a), mean probability of reporting the target location (b), mean probability of reporting a non-target (misbinding; c), and mean probability of guessing (d) as a function of set size. Shaded regions represent SEM.

significant; $p \geq 0.227$.

7. Discussion

The results of this experiment were broadly similar to Experiment One, in that there was an exponential increase in localisation error with set size (although this effect was slightly stronger in Experiment One), mirrored by a monotonic, exponential increase in guessing with set size. Critically, as with Experiment One, imprecision was stable between set sizes 2 and 6.

8. General discussion

The current experiments sought to examine how the pattern of recall errors in spatial working memory changed with set size when using a mouse response. Across two experiments, we found that localisation error increased exponentially, whereas imprecision significantly increased between set size 1 and 2 but was relatively stable between set size 2 and 6. These findings contrast with those reported by Schneegans and Bays (2016), who reported a linear relationship in localisation error and monotonic increase in imprecision with increasing set size.

The most probable explanation for the apparent discrepancy in the best fitting model of localisation error is that by jumping from a set size of 4 to a set size of 8, Schneegans and Bays (2016) lacked the granularity to detect the exponential relationship. The explanation for the discrepancy in the imprecision data is less obvious. One possibility is that it arises from differences in the mode of stimulus localisation. In the current experiments, participants responded using the mouse to direct the cursor to the remembered location on the screen. Schneegans and Bays' (2016) participants responded by pushing their finger along the surface upon which the memoranda appeared while position was monitored via an electromagnetic motion sensor. Cockburn et al. (2012) found that finger pointing responses were equally as accurate as mouse responses overall, but that errors with a mouse were less affected by the number of items present compared to finger pointing responses. This finding might be considered to be similar to our finding of a slower increase in imprecision across set sizes compared to Schneegans and Bays (2016).

One possible reason that finger pointing and mouse pointing produce subtly different patterns of errors in spatial working memory is that mouse pointing requires more complex visuomotor transformations than finger pointing because the localisation movement is on a different plane to the stimulus (the desktop rather than the screen), and in a different coordinate space. Transforming representations across different co-ordinate spaces is a noisy process (Golomb & Kanwisher, 2012), which might explain the exponential relationship found in localisation error. That is, as more items are to be remembered, the transformation becomes noisier due to limited cognitive resources being directed to each item (Bays et al., 2009). However, because spatial working memory is such an important cognitive mechanism for much of our daily behaviour (Manohar et al., 2017), it is inefficient to have this noise accumulate in a free-form manner, which is reflected in the slower increase in imprecision with set size after set size two. Rather, the noise might accumulate in terms of the other presented information that is less relevant for task completion. For example, participants were not required to retain a precise representation of colour to complete this spatial working memory task. It might be that the representation of colour was decreased in favour of boosting the precision with which the spatial locations are retained. As a consequence of this trade-off, when the probed item was presented, the binding information might not have been retrievable, resulting in increased misbinding errors and guessing,

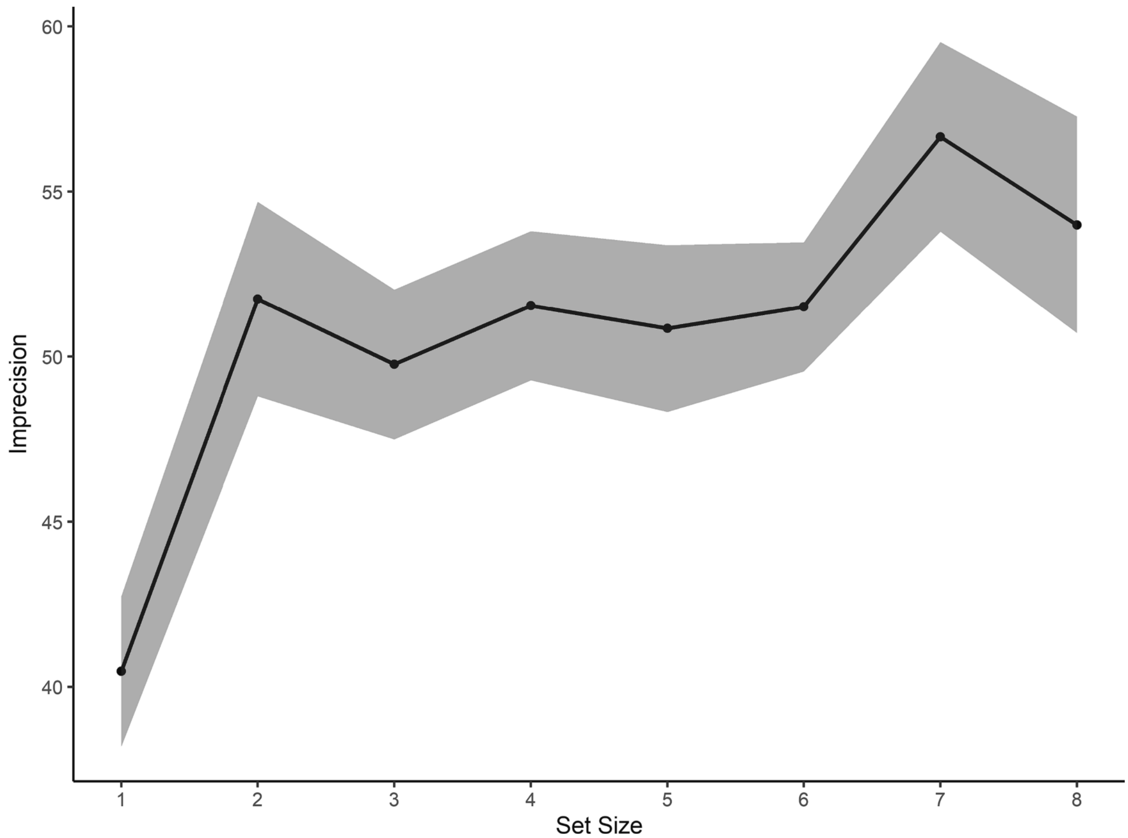

Fig. 8. Mean imprecision collapsed across Experiments 1 and 2 as a function of set size. Shaded regions represent SEM.

but with relatively constant imprecision across set sizes, as observed in both experiments. One way to directly examine this hypothesis is to directly compare the pattern of recall errors during pointing and mouse responses in this task.

There are three caveats to the current experiment which should be considered when interpreting these data. Firstly, there was some loss of data due to our exclusion criteria regarding eye movements. However, the medium and large effect sizes found for localisation error, imprecision, target responses, and misbinding are similar to previous findings (Pertzov et al., 2012; Schneegans & Bays, 2016) and the overall pattern of results did not change when data from all participants were analysed (see S2 and S4). Secondly, the distance of stimuli from fixation was not controlled in either the current experiment or Schneegans and Bays (2016), which may be important given there is evidence that attentional processing is less efficient with increasing set size and distance from fixation (Carrasco et al., 1995; Wolfe et al., 1998), and that changes in eccentricity influence VSWM encoding and maintenance ()(McAteer et al., 2023). Finally, Schneegans and Bays (2016) presented a fixation cross throughout each trial, which may have allowed for the global configuration of the array to be encoded, without the absolute positions of each item being encoded and retained (Jiang et al., 2000). Schneegans and Bays (2016) argued that the use of a landmark may have reduced the cognitive load of the task by promoting relational encoding of locations, leading to an improvement in overall VSWM performance. In the current study the landmark was removed after encoding which could have disrupted this global encoding strategy. However, while this disruption might produce differences in overall memory performance, it is not clear why it should lead to the flattening of the precision curve we observed between set size 2 and 8.

In summary, our finding of a monotonic increase in localisation error as set size increases is consistent with Schneegans and Bays (2016), demonstrating that memory for spatial locations becomes noisier as set size increases. Additionally, by using a larger range of set sizes, it was shown that localisation error increases exponentially with set size, rather than linearly, which supports that precision in VSWM is related to the proportion of resource directed to each item in VSWM. However, contrary to prior studies, imprecision did not significantly increase when set sizes was larger than 2. It is suggested that using a mouse response compared to a finger pointing response might underpin these results, because the information underwent a series of complex visuomotor transformations in order to make a mouse response at recall. These transformations would result in noise accumulation across all items in memory, which is reflected in the increase in localisation error. It is also speculated that there might be a protection mechanism in spatial working memory, which retains the precision of spatial locations for completion of upcoming complex tasks, by sacrificing the quality of the other information bound to that location, reflected in increasing misbinding errors. These findings demonstrate the validity of using mouse responses to estimate precision in spatial working memory.

CRediT authorship contribution statement

Siobhan M. McAteer: Conceptualization, Investigation, Writing – original draft, Writing – review & editing, Methodology, Software, Formal analysis. **Anthony McGregor:** Conceptualization, Supervision. **Daniel T. Smith:** Conceptualization, Supervision, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.visres.2023.108343.

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