



# Examining Working Memory Precision Estimates as an Individual Difference



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## Introduction

### WM Precision and Fluid Intelligence

Using a change detection paradigm, one study found that the resolution, or precision, of working memory (WM) representations did not significantly mediate the relationship between WMC and fluid intelligence (gF) (Fukuda et al. 2010).

### Continuous Report Task

The continuous report task provides parameters for the probability that a probed item is in WM, known as  $p_t$  and is a measure of WMC, and another for the precision of the probed item in memory, known as  $\kappa$  (Zhang & Luck 2008).

### Study Aim

To examine the relationship between working memory precision estimates from multiple versions of a continuous report task, gF, and WM capacity measures and how precision may relate or contribute uniquely to gF along with the relationship of  $\kappa$  between tasks. We also seek to examine whether WM precision is feature-specific or feature-general.

### Hypotheses

Consistent with previous findings, precision estimates ( $\kappa$ ) from the continuous report tasks will not have a significant relationship to gF scores. Capacity estimates from both tasks should be significantly correlated with gF scores consistent with prior research. We predict that  $\kappa$  across tasks will have a significant positive correlation.

## Method

### Task Procedure

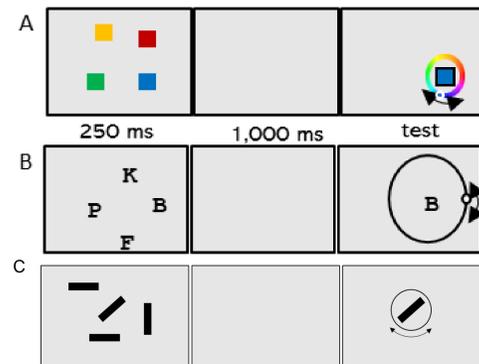
Participants (N = 222) completed three versions of a continuous report task and change detection tasks (color, space, and orientation), and three gF tasks (Raven Advanced Matrices, Number series, and Letter Sets).

### Data Analyses

Continuous report task data was analyzed via the standard mixture model (Zhang & Luck 2008) using the *mixtur* R package (Grange & Moore 2022).

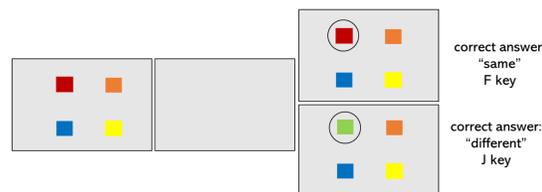
## Tasks

### Continuous Report Task



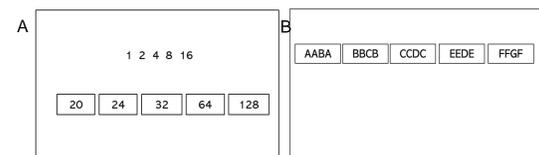
Note. A. Color continuous report task. B. Shape continuous report task. C. Orientation continuous report task.

### Change Detection Tasks



Note. Shape and orientation change detection tasks examples not shown but are similar in design.

### gF Tasks



Note. A. Number Series B. Letter Sets. Raven example not shown.

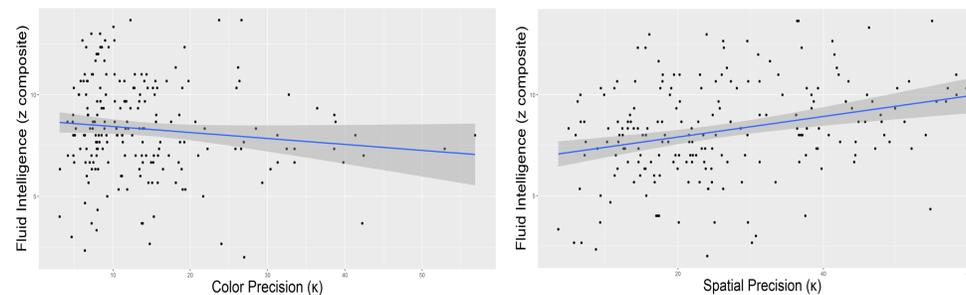
## Results & Discussion

Zero-order correlations among measures

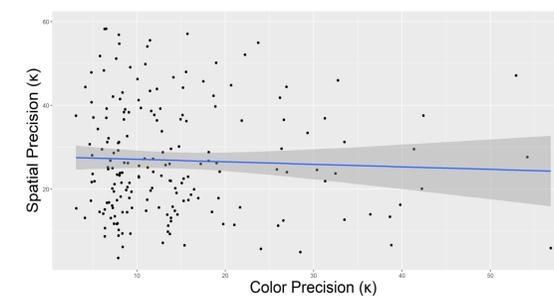
	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Color change detection $k$	<i>.86</i>									
2. Spatial change detection $k$	<b>.46</b>	<i>.85</i>								
3. Orientation change detection $k$	<b>.49</b>	<b>.57</b>	<i>.85</i>							
4. Color $P_t$	<b>.42</b>	<b>.35</b>	<b>.40</b>	<i>.87</i>						
5. Spatial $P_t$	<b>.39</b>	<b>.63</b>	<b>.58</b>	<b>.46</b>	<i>.84</i>					
6. Color $\kappa$ (precision)	<i>.02</i>	<i>.002</i>	<i>.02</i>	<b>-.31</b>	<i>-.05</i>	<i>.46</i>				
7. Spatial $\kappa$ (precision)	<i>.22</i>	<i>.16</i>	<i>.29</i>	<i>.25</i>	<i>.08</i>	<i>-.04</i>	<i>.60</i>			
8. Raven	<i>.28</i>	<i>.32</i>	<i>.36</i>	<i>.29</i>	<i>.26</i>	<i>-.11</i>	<i>.28</i>	<i>.75</i>		
9. Letter sets	<i>.23</i>	<i>.31</i>	<i>.34</i>	<i>.28</i>	<i>.37</i>	<i>-.07</i>	<i>.16</i>	<i>.26</i>	<i>.79</i>	
10. Number series	<i>.33</i>	<i>.23</i>	<i>.23</i>	<i>.19</i>	<i>.21</i>	<i>-.08</i>	<i>.23</i>	<i>.42</i>	<i>.46</i>	<i>.76</i>
11. Fluid intelligence ( $z$ composite)	<i>.31</i>	<i>.36</i>	<i>.39</i>	<i>.35</i>	<i>.35</i>	<i>-.12</i>	<i>.29</i>	<i>.76</i>	<i>.74</i>	<i>.79</i>

Note.  $k$  = capacity estimate,  $P_t$  = probability of target in memory,  $\kappa$  = kappa (precision parameter). Bolded correlations are significant at  $p < .05$ . Split-half reliabilities are listed in italics along diagonal.

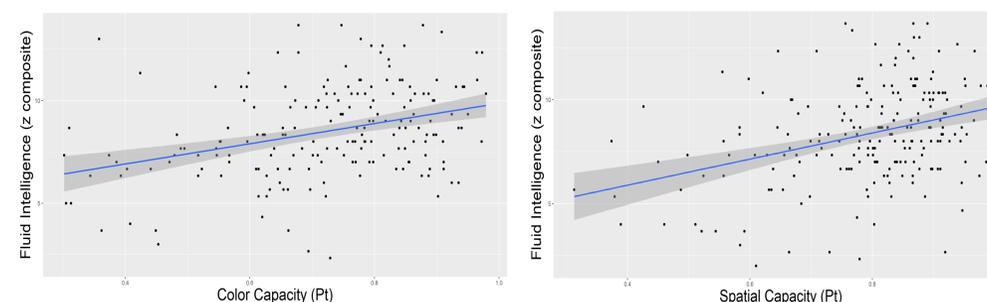
### Relationship between Precision ( $\kappa$ ) and Fluid Intelligence (gF)



### Relationship between Color and Spatial Precision ( $\kappa$ )



### Relationship between Capacity ( $P_t$ ) and Fluid Intelligence (gF)



We found that color precision was not significantly correlated to individual gF and gF composite scores, however, spatial precision was significantly related to all gF measures.

As expected, change detection and continuous report capacity measures,  $k$  and  $p_t$  respectively, all had a significant positive correlation with gF measures.

We found a weak, non-significant correlation between color and spatial precision, suggesting that WM precision may not be a feature-general construct.

We examined a latent factor model (where we loaded capacity measures to a capacity factor, gF scores to a fluid intelligence factor, and  $\kappa$  measures to a precision factor) and, as expected, we found it had poor fit, ( $\chi^2(32) = 91.79$ ,  $p < .001$ , CFI = 0.83, RMSEA = .105, 90% CI = [0.08, 0.13], SRMR = .07).

## Conclusion

While color precision did not significantly relate to gF, spatial precision did, suggesting that precision of WM representation is not a feature-general ability.

More research will need to be done to explore alternate feature-dimensions of continuous report WM tasks to better understand the relationship between WM precision and gF, as well as its relationship with other known associates of WMC.

## References

Fukuda, K., Vogel, E., Mayr, U., Awh, E., (2010). Quantity, not quality: the relationship between fluid intelligence and working memory capacity. *Psychonomic Bulletin & Review* 17, 673–679.

Grange, J.A., Moore, S.B. (2022) mixtur: An R package for designing, analysing and modelling continuous report visual short-term memory studies. *Behav Res* 54, 2071–2100.

Zhang, W., & Luck. S. J., (2008). Discrete fixed-resolution representations in visual working memory. *Nature*. 453, 233-235.