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Placekeeping Ability as a Component of Fluid Intelligence: Not Just Working Memory Capacity

ALEXANDER P. BURGOYNE, DAVID Z. HAMBRICK, and ERIK M. ALTMANN
Michigan State University

The question of what cognitive processes contribute to fluid intelligence (Gf)—the ability to solve novel problems—continues to be central in intelligence research. Here, we considered the contribution of placekeeping, which is the ability to perform a sequence of steps in a prescribed order without omissions or repetitions. Placekeeping plays a role in problem solving but also rests on the ability to remember past performance, so it may simply reduce to working memory capacity (WMC). To investigate this possibility, we evaluated whether placekeeping accounts for individual differences in Gf above and beyond WMC. Hierarchical regression analyses revealed that placekeeping ability accounted for 12% of the variance in Gf above and beyond WMC. By contrast, WMC accounted for only 2% of the variance in Gf above and beyond placekeeping ability. Structural equation modeling revealed that placekeeping ability and WMC are distinct at the latent variable level, and together they accounted for 77% of the variance in Gf. However, whereas placekeeping ability significantly predicted Gf in the structural equation model, WMC did not. In general, the results suggest that placekeeping ability is distinct from WMC and contributes substantially to individual differences in Gf.

KEYWORDS: placekeeping ability, fluid intelligence, working memory

A wide range of tasks that people perform at home and in the workplace involve a kind of linear thinking in which the task performer must carry out a sequence of steps in a prescribed order, without repeating or omitting steps. We refer to this cognitive function as placekeeping ability. In this study, we examine the relationship between placekeeping ability and fluid intelligence (Gf), which captures the ability to solve novel problems and adapt to new situations (Engle, Tuholski, Laughlin, & Conway, 1999).

At a theoretical level, one reason to think that placekeeping ability is related to Gf is that solving novel problems depends on a kind of linear thinking. Newell and Simon (1972; Newell, 1990) characterized problem solving in terms of a search process in which the problem solver applies sequences of operators to transform mental problem states and periodically sets, suspends, and resumes goals organized in a hierarchical mental structure. For such processing to lead to solutions efficiently, the system must be able to keep its place in sequences of operators and within hierarchical goal structures. Skipping an element could mean missing a path to a solution, and repeatedly evaluating a failed path

is inefficient and could also lead to missing a solution if solution time is limited. The role of successful management of operators and goals in problem solving was highlighted in a study of performance on Raven's Progressive Matrices (Carpenter, Just, & Shell, 1990). Better goal management, implemented in a computational cognitive model, accounted for better performance on Raven's Progressive Matrices (a test of Gf).

In previous empirical work, we have shown that placekeeping accounts for a significant amount of variability in Gf (Hambrick & Altmann, 2015; Hambrick, Altmann, & Burgoyne, 2018). And yet placekeeping might not be a distinct cognitive ability. A central requirement of this kind of linear thinking is the ability to remember past performance, in order to distinguish work that has been done from work that remains to be done. Conceivably, then, placekeeping is simply an expression of working memory capacity (WMC), a construct that in past studies has accounted for a large amount of the variance in Gf (e.g., Kane et al., 2004; Kane, Hambrick, & Conway, 2005). At the same time, in a cognitive model of placekeeping that we have developed, long-term memory also plays a central role, because it represents the linear sequences that the system has to follow (Altmann & Hambrick, 2017; Altmann, Trafton, & Hambrick, 2017). Accordingly, there is reason to think that placekeeping is distinct from WMC.

In this study, we asked whether placekeeping is distinct from WMC by empirically testing whether it accounts for individual differences in Gf above and beyond WMC. We had participants complete tests of placekeeping ability, WMC, and Gf, selecting tests that tap a range of underlying mechanisms. We then used hierarchical regression analyses and structural equation modeling (SEM) to assess the relative contributions of placekeeping ability and WMC to Gf.

STUDY

METHOD

Participants

The participants were 283 undergraduate students recruited from the participant pool at Michigan State University over the course of one semester.

Procedure and Materials

The study took place in two sessions. In each session, participants completed a test of placekeeping ability, a test of WMC, and a test of Gf (Table 1). The tests were selected to measure different kinds of processing within each construct. As measures of placekeeping, UNRAVEL taps verbal and amodal mechanisms, whereas Letter Wheel taps primarily spatial mechanisms. As measures of WMC, Operation Span uses verbal memoranda, whereas Symmetry Span uses visuospatial memoranda. Finally, as measures of Gf, Raven's Progressive Matrices taps visuospatial reasoning, whereas Letter Sets taps verbal/numerical reasoning.

UNRAVEL.

Participants repeatedly perform a sequence of seven two-alternative forced choice (2AFC) tasks, in an order specified by the acronym UNRAVEL (Figure 1). On each step of the sequence, the participant responds, using the keyboard, to a randomly generated, multidimensional stimulus to which any of the seven 2AFC rules could be applied and must therefore remember which step is currently correct. Participants are periodically interrupted by a typing transcription task. In the transcription task, the multidimensional stimulus disappears, and a string of random letters appears. Participants must type the string correctly. After two transcription trials, a new multidimensional stimulus appears. Participants must resume implementing the 2AFC rules, at the place in the acronym where they left off. In theoretical terms, these interruptions by the transcription task map to interruptions in problem solving experienced when the problem solver must decompose a goal into subgoals, achieve the subgoals, and then resume the suspended goal correctly.

Participants completed two blocks of UNRAVEL. Each block consisted of approximately 66 2AFC trials and 10 interruptions. A trial spanned the duration from the onset of the multidimensional stimulus display until the participant responded via the keyboard. "Response time" reflects the average response time for accurate trials, and "error rate" reflects the proportion of trials in which the participant implemented the wrong rule, with respect to the previously implemented rule in the sequence. Both response time and error rate are performance measures indexing placekeeping ability. The coefficient α was .74 for response time and .59 for error rate, as computed using the two blocks of the task. For a further de-

TABLE 1. Tests Completed During Study Sessions

	Placekeeping	Working memory capacity	Fluid intelligence
Session 1	UNRAVEL	Operation span	Letter sets
Session 2	Letter Wheel	Symmetry span	Raven's progressive matrices

(a) Sample stimuli for UNRAVEL task:

Stimulus 1   Stimulus 2

(b) Choice rules and candidate responses for UNRAVEL task, and responses to the stimuli in (a)

Step	Candidate responses		Choice rules	Responses to Stimulus 1	Responses to Stimulus 2
U	u	i	character is Underlined or in Italics	u	i
N	n	f	letter is Near to or Far from start of alphabet	n	f
R	r	y	character is Red or Yellow	r	y
A	a	b	character is Above or Below the box	a	b
V	v	c	letter is Vowel or Consonant	v	c
E	e	o	digit is Even or Odd	o	e
L	l	m	digit is Less than or More than 5	l	l

(c) Sample stimulus for the transcription task:
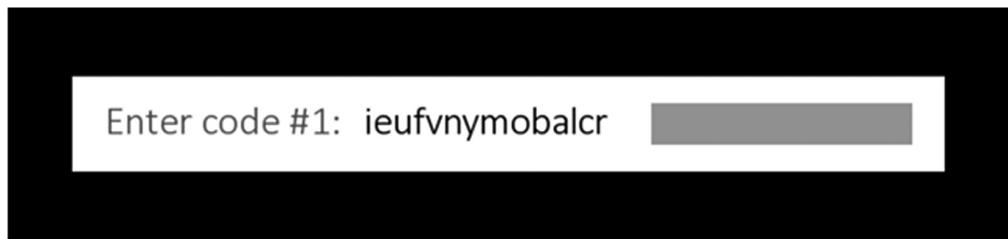
Enter code #1: ieufvnymobalcr

FIGURE 1. UNRAVEL. (a) Two sample stimuli for the UNRAVEL task (the *A* is presented in red, and the *2* in yellow). (b) Response mappings for the UNRAVEL task, along with responses for the two sample stimuli shown in (a). (c) Sample stimulus for the transcription task

scription of UNRAVEL, see Altmann, Trafton, and Hambrick (2014).

LETTER WHEEL.

Participants are presented with nine randomly generated letters circumscribed around a circle (Figure 2). They must alphabetize sets of three adjacent letters using the keyboard. Every trial, the spatial location of the set of three to-be-alphabetized letters shifts clockwise one position around the circle, and all of the letters are randomly generated again. Participants are periodically interrupted by a counting task in which the letter wheel is replaced by sets of asterisks appearing in random locations. Participants must count the asterisks, responding using the keyboard. After they successfully complete five counting trials, the letter wheel reappears. Participants must resume alphabetizing sets of letters, at the spatial location on the wheel where they left off. The counting task serves the same role here as the transcription task in UNRAVEL, in terms of burdening memory for past performance.

Participants completed two blocks of Letter Wheel. Each block consisted of approximately 63 alphabetizing trials and 8 interruptions. A trial spanned the duration from the onset of the letter wheel display until the participant responded by entering three letters using the keyboard. "Response time" reflects the average response time for accurate trials, and "error rate" reflects the proportion of trials in which the participant alphabetized the wrong set of three letters, with respect to the previously alphabetized set of three letters. The coefficient α was .91 for response time and .71 for error rate, as computed using the two blocks of the task.

OPERATION SPAN.

Participants solve math equations and remember a letter that follows each equation. We used a shortened version of the task developed by Foster et al. (2015). After a series of trials, participants recall the letters in the presented order. There were five equation–letter trials, with one trial per set size. The measure was the number of correct letters recalled. The coefficient α for Operation Span was .54.

SYMMETRY SPAN.

Participants make symmetry judgements about patterns and remember the location of a square that appears after each pattern (Unsworth, Heitz, Schrock, & Engle, 2005). After a series of trials, participants recall the location of the squares in the presented order. There were 12 sets of pattern–square trials, 3 at each set size. The measure was the number of correct square locations recalled. The coefficient α for Symmetry Span, based on average performance at each set size, was .69.

LETTER SETS.

Presented with five sets of four letters (e.g., *ABCD*) arranged in a row, participants choose the set that does not follow the same pattern as the other four (Ekstrom, French, Harman, & Dermen, 1976). Participants were given 5 min to complete 20 items. The measure was the number correct. The coefficient α for Letter Sets was .64.
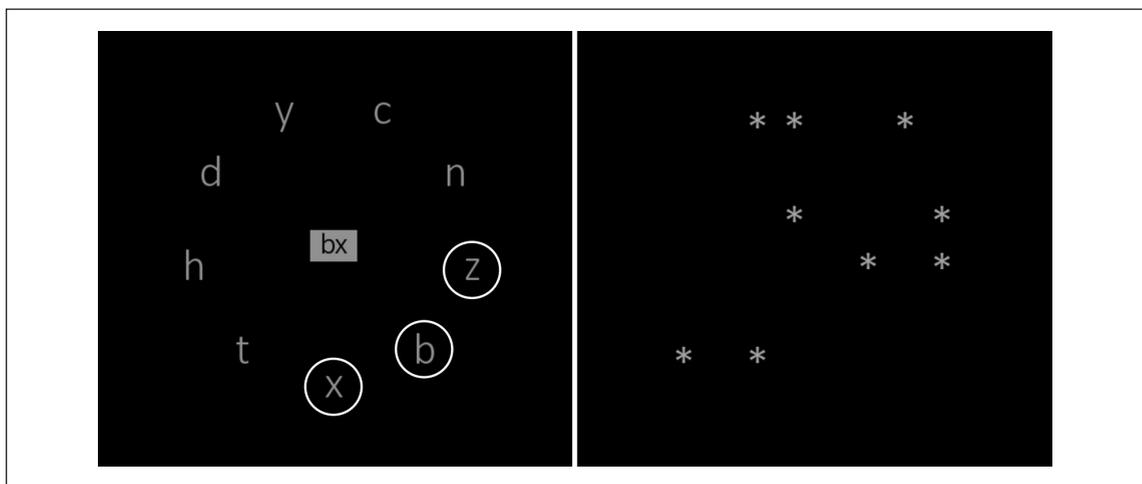

FIGURE 2. Letter Wheel. Left: alphabetizing task. Circles illustrating the current trial are visible only on the first trial of each block. On the next trial, the participant will alphabetize letters that appear where *b, x,* and *t* are currently. Right: counting task

Participants are presented with a set of patterns. The pattern in the lower-right is missing. Participants choose the alternative that best completes the set. Participants were given 10 min to complete the 18 odd-numbered items from Raven's Advanced Progressive Matrices (Raven, Raven, & Court, 1998). The measure was the number correct. The coefficient α for Raven's was .66.

Data Screening

Of 283 participants, 22 were excluded because their error rate on UNRAVEL or Letter Wheel was not significantly better than chance-level performance. Of the 261 remaining participants, 13 were excluded due to outlying scores (i.e., a score for a measure differing by more than 3.5 standard deviations from the sample mean). Data from the remaining 248 participants were submitted to the analyses described next. Four participants did not have scores on either Symmetry Span or Letter Sets due to technical difficulties; these values were marked as missing. Data are available on the Open Science Framework (https://osf.io/ndquz/?view_only=87cd1ad87c9e4fabba3e21c609ce9a14).

Composite Variables

We created composite variables by averaging z scores for the measures of Gf (Letter Sets and Raven's Matrices), WMC (Operation Span and Symmetry Span), placekeeping error rate (UNRAVEL error rate and Letter Wheel error rate), and placekeeping response time (UNRAVEL response time and Letter Wheel response time).

RESULTS

Descriptive statistics for the measures are presented in Table 2. For both measures of placekeeping ability, there was a considerable amount of variability across participants in error rate (0% to 55.7%, $M = 10.1\%$, $SD = 10.6\%$ for UNRAVEL; 0% to 56.7%, $M = 13.2\%$, $SD = 10.0\%$ for Letter Wheel) and response time (2.3 s to 6.3 s, $M = 3.7$ s, $SD = 0.7$ s for UNRAVEL; 1.7 s to 7.6 s, $M = 4.9$ s, $SD = 1.0$ s for Letter Wheel).

Correlations are presented in Table 3. Measures of placekeeping ability correlated negatively with the other cognitive ability measures, indicating that high levels of placekeeping ability were associated with superior performance in the other cognitive ability tests. Furthermore, there were moderate correlations between measures of placekeeping performance from UNRAVEL and Letter Wheel: $r = .30$ ($p < .001$) for error rate, $r = .37$ ($p < .001$) for response time.

Hierarchical Regression Analyses

To estimate the relative contributions of placekeeping ability and WMC to Gf, we conducted two hierarchical regression analyses predicting the Gf composite. For Model 1, we entered the WMC composite in Step 1 and the placekeeping composites in Step 2. For Model 2, we entered the placekeeping composites in Step 1 and the WMC composite in Step 2. Thus, Model 1 assessed whether placekeeping ability contributed to Gf above and beyond WMC, whereas Model 2 assessed whether WMC contributed to Gf above and beyond placekeeping ability.

TABLE 2. Descriptive Statistics

Measure	N	M	SD	Skewness	Kurtosis	α
Operation Span	248	17.77	5.22	−0.83	0.28	.54
Symmetry Span	245	29.09	7.18	−0.57	−0.18	.69
Letter Sets	247	10.18	2.81	0.01	−0.03	.64
Raven's Matrices	248	8.37	3.04	0.05	−0.26	.66
UNRAVEL error rate	248	10.13	10.64	2.20	5.28	.59
UNRAVEL response time	248	3.72	0.68	0.68	0.99	.74
Letter Wheel error rate	248	13.23	9.98	1.70	3.81	.71
Letter Wheel response time	248	4.92	1.01	0.28	0.01	.91

TABLE 3. Correlation Matrix

	1	2	3	4	5	6	7	8
1. Operation Span	—							
2. Symmetry Span	.23	—						
3. Letter Sets	.07	.29	—					
4. Raven's Matrices	.06	.28	.26	—				
5. UNRAVEL error rate	−.13	−.22	−.23	−.25	—			
6. UNRAVEL response time	−.09	−.08	−.10	−.12	.10	—		
7. Letter Wheel error rate	−.14	−.39	−.09	−.25	.30	−.03	—	
8. Letter Wheel response time	−.04	−.12	−.30	−.17	.06	.37	−.16	—

Note. *Listwise* n *= 244. Correlations with an absolute magnitude greater than .12 are statistically significant at* p *< .05.*

The results are presented in Table 4. Placekeeping ability accounted for 11.9% of the variance in Gf above and beyond WMC, whereas WMC accounted for only 2% of the variance in Gf above and beyond placekeeping ability.

Structural Equation Modeling

We further examined the contribution of placekeeping ability and WMC to Gf at the latent variable level using SEM. Latent variables capture variance common to a set of indicators and are thus free of mea-

TABLE 4. Hierarchical Regression Analyses With WMC and Placekeeping Ability Predicting Gf

Model 1: DV = Gf	ΔR^2	ΔF	β	t	sr^2
Step 1	.076	20.37***			
WMC			.28	4.51***	.08
Step 2	.119	18.00***			
Placekeeping error rate			−.27	−4.32***	.06
Placekeeping response time			−.26	−4.45***	.07
Total	.195	19.73***			
Model 2: DV = Gf	ΔR^2	ΔF	β	t	sr^2
Step 1	.175	26.07***			
Placekeeping error rate			−.32	−5.48***	.10
Placekeeping response time			−.28	−4.81***	.08
Step 2	.020	5.99*			
WMC			.15	2.45*	.02
Total	.195	19.73***			

Note. *Model 1: Step 1* df *= 1, 246; Step 2* df *= 2, 244. Model 2: Step 1* df *= 2, 245; Step 2* df *= 1, 244.* β, *standardized regression coefficient;* sr², *squared semipartial correlation, reflecting independent contribution of the predictor to Gf.* βs, ts, *and* sr²s *are presented for each step. Gf = fluid intelligence; WMC = working memory capacity.*
*p < .05. **p < .01. ***p < .001.

surement error. Thus, this analysis permits us to shift our conclusions from the level of observed variables and closer to the theoretical constructs of interest.

We first tested whether placekeeping ability and WMC were distinct from one another at the level of latent variables. Specifically, we created a confirmatory factor analysis (CFA) model with latent factors for placekeeping error rate (indicators: UNRAVEL error rate for Blocks 1 and 2, and Letter Wheel error rate for Blocks 1 and 2), WMC (indicators: Symmetry Span and Operation Span), and placekeeping response time (indicators: UNRAVEL response time for Blocks 1 and 2, and Letter Wheel response time for Blocks 1 and 2). The CFA model is depicted in Figure 3.

The model fit the data well, $\chi^2(28) = 40.54$, $p = .059$, comparative fit index (CFI) = .981, normed fit index (NFI) = .945, root mean square error of approximation (RMSEA) = .043. WMC correlated significantly and substantially with placekeeping error rate, $r = -.61$, $p < .001$, but not with placekeeping response time, $r = -.18$, $p = .086$. Placekeeping error rate and placekeeping response time were not significantly correlated, $r = -.17$, $p = .075$. To test whether WMC and placekeeping ability were distinct in the model, we performed a test for redundancy (Kline, 2011, p. 243). That is, we constrained the correlation of WMC with placekeeping error rate and placekeeping response time to 1.0 and compared the fit of each constrained model to the fit of the unconstrained model. As shown in Table 5, the constrained models fit significantly worse by a chi-square difference
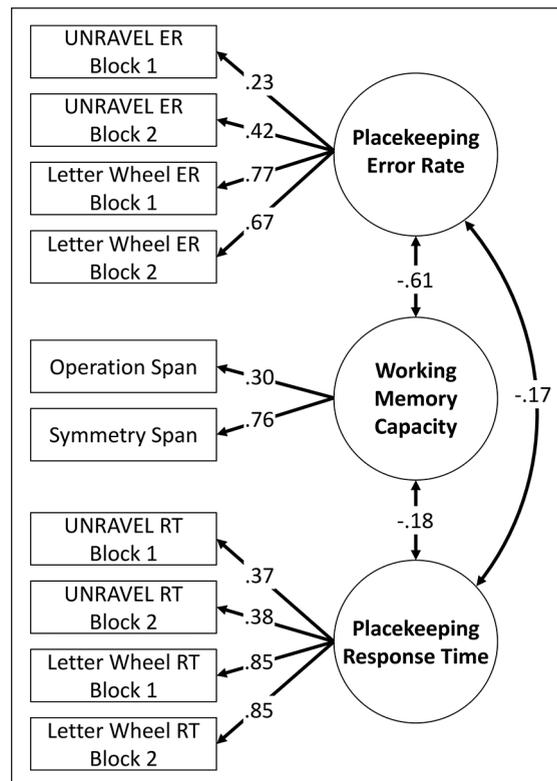

FIGURE 3. Confirmatory factor analysis with placekeeping error rate, working memory capacity, and placekeeping response time. ER = error rate; RT = response time. The following error terms were allowed to correlate to account for common method variance: UNRAVEL ER Block 1 with UNRAVEL ER Block 2 ($r = .37$), Letter Wheel ER Block 1 with Letter Wheel ER Block 2 ($r = .08$), UNRAVEL RT Block 1 with UNRAVEL RT Block 2 ($r = .54$), Letter Wheel RT Block 1 with Letter Wheel RT Block 2 ($r = .43$)

TABLE 5. Comparison of Confirmatory Factor Analysis Models

Model	Chi-square	Comparative fit index	Normed fit index	Root mean square error of approximation	Chi-square difference test
Unconstrained	$\chi^2(28) = 40.54$, $p = .059$	.981	.945	.043	—
Placekeeping error rate constrained with WMC	$\chi^2(29) = 45.76$, $p = .025$	.975	.937	.048	$\chi^2(1) = 5.22$, $p = .022$
Placekeeping response time constrained with WMC	$\chi^2(29) = 53.63$, $p = .004$	.964	.927	.059	$\chi^2(1) = 13.09$, $p < .001$

Note. Chi-square difference test compares the fit of each constrained model to the unconstrained model.

test (p = .022 and p < .001, respectively). The other fit statistics also favored the unconstrained model. This indicates that WMC and placekeeping ability are dissociable at the latent variable level.

In the second step of the SEM, we estimated the relative contribution of placekeeping error rate, placekeeping response time, and WMC to Gf. In this model, we added a latent factor representing Gf (indicators: Raven's Matrices and Letter Sets) and then predictor paths from placekeeping error rate, placekeeping response time, and WMC to Gf. Results are presented in Figure 4. The model fit the data well, $\chi^2(44)$ = 63.04, p = .031, CFI = .975, NFI = .925, RMSEA = .042, and the predictors accounted for 77.1% of the variance in Gf. Placekeeping response time was a significant predictor of Gf (standardized regression weight = −.56, p = .001), as was placekeeping error rate (standardized regression weight = −.51,

p = .044). WMC was not a significant predictor of Gf (standardized regression weight = .26, p = .303).

Supplemental Analyses

Recently, based on item response theory analyses, Draheim, Harrison, Embretson, and Engle (2018) argued that Operation Span is "not suitable for above average ability samples" (p. 116), whereas Symmetry Span is "much better at measuring higher ability subjects" and "superior to operation span in many ways" (p. 128). Directly relevant to the present research, Draheim et al. observed that Symmetry Span correlates more highly with Gf than Operation Span does in high-ability samples (Symmetry Span average r = .25, Operation Span average r = .14; see Table 8 of Draheim et al., 2018). Our university sample was above average in cognitive ability; the average ACT score for the university is 26, which is nearly 1 stan-
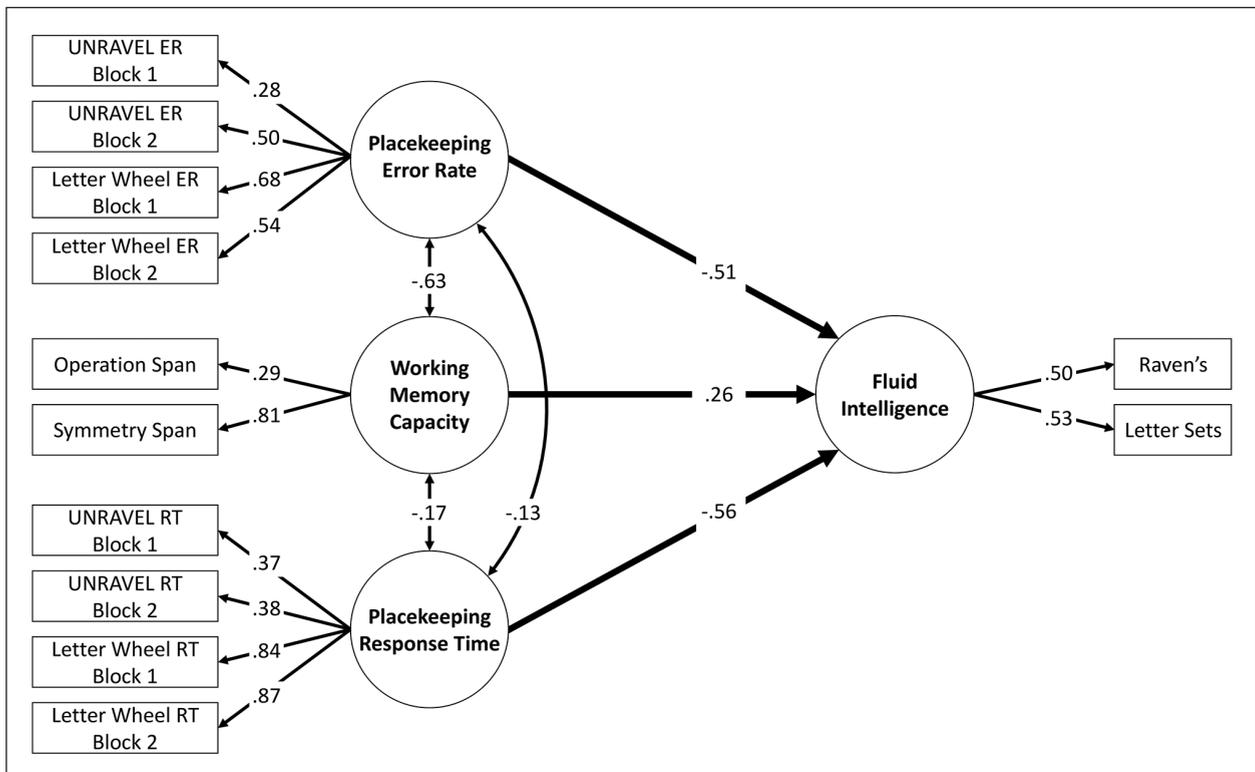

FIGURE 4. Structural equation model with placekeeping error rate, working memory capacity, and placekeeping response time accounting for 77.1% of the variance in fluid intelligence. ER = error rate; RT = response time. The following error terms were allowed to correlate to account for common method variance: UNRAVEL ER Block 1 with UNRAVEL ER Block 2 (r = .34), Letter Wheel ER Block 1 with Letter Wheel ER Block 2 (r = .30), UNRAVEL RT Block 1 with UNRAVEL RT Block 2 (r = .54), Letter Wheel RT Block 1 with Letter Wheel RT Block 2 (r = .42)

dard deviation higher than the national average for this standardized college admissions test (M = 20.9, SD = 5.7; ACT, 2018). Furthermore, consistent with Draheim et al.'s point, Symmetry Span correlated more highly with the Gf measures in this sample than Operation Span did (average r = .29 vs. .07).

With the preceding in mind, to ensure that our conclusions were unaffected by use of Operation Span as a measure of WMC, we repeated the preceding analyses without Operation Span and using only Symmetry Span. The results of the hierarchical regression analyses were virtually identical to those reported in Table 4. Symmetry Span added 5.0% to the prediction of Gf, above and beyond placekeeping ability. Conversely, placekeeping ability added 9.5% to the prediction of Gf, above and beyond Symmetry Span. The results of the SEM, with set sizes two to five from Symmetry Span as four indicators of the WMC factor, were slightly different from those reported in Figure 4, but in a way that strengthens our conclusions: The effects of both placekeeping error rate (standardized regression weight = –.53, p = .012) and placekeeping response time (standardized regression weight = –.56, p < .001) on Gf were statistically significant, whereas the effect of WMC on Gf was still nonsignificant (standardized regression weight = .23, p = .226). The model fit the data well, $\chi^2(67)$ = 91.54, p = .025, CFI = .974, NFI = .911, RMSEA = .039, and the predictors accounted for 76.4% of the variance in Gf.

Summarized, even when we conducted our analyses using what has been deemed to be a superior measure of WMC for samples above average in ability (Draheim et al., 2018), the results of our study indicate that placekeeping ability may be more fundamental in predicting individual differences in Gf than WMC, raising an important theoretical question that we begin to address below.

DISCUSSION

In this study, we asked whether placekeeping contributes to individual differences in Gf, above and beyond WMC. The question is relevant because sequential processing supported by placekeeping plays a central role in problem solving. And yet, because operations such as returning to suspended

subgoals in a problem-solving hierarchy arguably rest heavily on working memory, it was necessary to evaluate the contributions of placekeeping relative to WMC, which has been found to account for a substantial amount of variability in Gf (e.g., Kane et al., 2005).

Our results indicate that placekeeping ability does indeed contribute to Gf above and beyond WMC. That is, hierarchical regression analyses revealed that placekeeping ability accounted for 11.9% of the variance in Gf above and beyond WMC, whereas WMC accounted for only 2% of the variance in Gf above and beyond placekeeping ability. Structural equation modeling further revealed that placekeeping ability and WMC are distinct at the latent variable level and together accounted for 77.1% of the variance in Gf. However, whereas placekeeping ability significantly predicted Gf in the structural equation models, WMC did not. These results held even when we used a measure of WMC deemed appropriate for samples above average in ability (i.e., Symmetry Span; Draheim et al., 2018).

These results suggest, at the very least, that the cognitive operations involved in placekeeping and complex span tasks do not completely overlap. Of potentially greater theoretical import is the asymmetry in incremental validity between placekeeping ability and complex span with respect to Gf. If this asymmetry turns out to replicate robustly in future studies, it would raise an important theoretical question about the nature of the underlying mechanisms. Our previous theoretical work suggests that placekeeping involves an interaction between episodic and semantic memory, in which episodic memory for past performance is used to index semantic memory for the sequence of steps that the task performer must follow (Altmann et al., 2017). In one possible mapping to the Raven's task, which was one of our measures of Gf, episodic memory would store solutions that had been explored, whereas semantic memory would organize the different rules that people hypothetically use to generate new potential solutions (Carpenter et al., 1990). In complex span tasks, episodic memory plays a role in storing the memoranda, but there seems to be no corresponding role for semantic memory. Accordingly, the unique contribution of placekeeping in accounting for variance in Gf may lie in the interplay

between two memory systems that both play a role in solving novel problems.

Limitations

We note two limitations of this study. The first is that we administered only two tests of each construct (see Table 1). The use of two indicator measures is not uncommon in SEM studies of this kind (see, e.g., Engle et al., 1999), and two tests per construct were enough to require multiple sessions per participant. Nonetheless, based on the evidence we provide here that placekeeping plays an important role in Gf, a replication with three tests per construct—which would also require developing or adapting a new test of placekeeping—would be a worthwhile investment.

The second limitation concerns the negligible correlation between Operation Span and measures of Gf (Table 3), which runs counter to most research examining the relationship of WMC and Gf. As we noted earlier, recent work has suggested that Operation Span has poor discriminant validity (Draheim et al., 2018), and our reduced version of the task may have compounded the problem (qualifying the results of Foster et al., 2015). One interesting possibility is that the lack of a correlation between Operation Span and specifically Raven's (Table 3) is linked to the fact that they were administered on separate days (Table 1); a given participant could have been more motivated or attentive during one testing session than the other. Alternatively, our Operation Span results are another reason to invest in a replication with three indicators of all measures.

Conclusion

Taken together, the results suggest that placekeeping ability is distinct from WMC and contributes substantially to individual differences in Gf. An important goal for future research is to conduct experiments to identify the exact mechanisms accounting for the relationship between placekeeping ability and Gf. Together with the type of correlational research reported here, this research promises to shed new light on the underpinnings of human intelligence.

Address correspondence about this article to Alexander Burgoyne, Department of Psychology, Michigan State University, 316 Physics Road, Suite 48, East Lansing, MI 48824 (e-mail: burgoyn4@msu.edu).

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