Differential involvement of working memory capacity and fluid intelligence in verbal associative learning as a possible function of strategy-use

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A brief presentation can be found here: <https://youtu.be/wVkJyPzugOo>

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Abstract

The paired-associate paradigm has a long history of use in basic and applied research on human memory and learning. A number of studies have shown that individuals differ in the strategies they use to encode information in paired-associate tasks and, importantly, that strategies differ in their effectiveness. What is not so well documented is how different strategies may affect the cognitive processes assessed by paired-associate tasks. In this study, we submit archival data to distributional and latent class analyses to infer strategy-use and classify individuals as elaborators or non-elaborators. We then used regression analyses within subgroups to identify differences in dependence on fluid intelligence and working memory capacity. To the extent that our classification of individuals was accurate, the results suggest that paired-associate learning is more reliant on fluid intelligence when elaborative rehearsal is utilized and more reliant on working memory capacity when using non-elaborative strategies. To offer further evidence of the validity of our approach, we also investigated correlations between strategy-use and fluid intelligence and working memory capacity. In accord with prior research, we found that cognitive abilities were positively correlated with what we infer to be differences in strategy-use. That the cognitive processes assessed by verbal paired-associate tasks may vary as a function of strategy-use should be a concern for all researchers and practitioners who use such tasks.

Introduction

In the analysis of any cognitive task, one should avoid averaging over strategies because processes either are different or are deployed in different ways.

Hintzman (2011, p. 255)

...control processes [such as encoding strategies] are such a pervasive and integral component of human memory that a theory which hopes to achieve any degree of generality must take them into account.

Atkinson and Shiffrin (1968, p. 191)

The paired-associate paradigm has a long history of use in basic and applied research on human memory and learning (e.g., Calkins, 1898). In a paired-associate task, individuals attempt to learn some number of item pairs (e.g., words in one's native language paired with foreign words); at recall, one half of a pair is presented (e.g., a foreign word) and one attempts to recall the associated item (e.g., the native language word). In basic research, paired-associate tasks are used to better understand human memory (e.g., Blumenfeld et al., 2011; Eichenbaum & Bunsey, 1995) and language learning in children and adults (e.g., Gathercole et al., 1997; K. I. Martin & Ellis, 2012). In applied settings they are used to assess language learning aptitude (e.g., Li, 2015; Linck et al., 2013), intellectual functioning (e.g., Wechsler, 1997a, 1997b), and as prognostic indicators of memory related disorders such as Alzheimer's disease (e.g., Erickson & Scott, 1977; Fowler et al., 2002).

Given the utility and ubiquity of paired-associate tasks, it is crucial that researchers and other professionals understand what it is they are measuring and how various factors may affect performance and therefore the validity of paired-associate tasks. Among the myriad factors that affect performance is strategy use (Jenkins, 1979). It is well documented that individuals differ in their use of strategies (Clark et al., 1960; Dunlosky & Hertzog, 2001; C. J. Martin et al., 1965) and that strategy-use greatly affects

performance (Bailey et al., 2008; Bradley & Glenberg, 1983; Craik & Tulving, 1975). What is not so well documented is how these different strategies may affect the cognitive processes assessed by paired-associate tasks (cf. Kyllonen et al., 1991; Tirre, 1991). Given the wealth of research on the former, we focus on the latter. Specifically, we ask whether reliance on working memory capacity and fluid intelligence change as a function of encoding strategy. To investigate this question, we first investigated whether there was evidence of strategy-type preference by conducting distributional and latent class analyses. We then used the results of the latent class analyses to infer strategy-use and classified individuals according to the type of strategies they were likely using. Next we investigated relations between paired-associate performance and indicators of working memory capacity and fluid intelligence within identified classes (i.e., subgroups). Finally, to further support our approach, we also investigated relations between inferred strategy-use and fluid intelligence and working memory capacity.

Background

There are many encoding strategies one can employ in a paired-associate task but some are more effective than others (Bower & Winzenz, 1969; Shaughnessy, 1981). In general, the most effective strategies elaborate upon the material under study and in doing so induce relationships (Kyllonen et al., 1991). For example, given a pair such as *tree-rock*, one may use visual imagery and imagine an idyllic scene with a rock next to a tree or one may generate a sentence such as, “the petrified tree looked and felt like a rock.” In the first case, *tree* and *rock* were both associated with nature, beauty, serenity, and thus to each other, as trees and rocks both exist in nature and potentially next to each other. In the second case, the terms were associated with each other via an established and likely unique semantic relationship: a petrified tree *is a* rock. These elaborations may serve to make the memory more distinct and therefore shield it from interference, in turn making it more likely to be recalled (Moscovitch & Craik, 1976) and/or elaborations may provide a network of pathways that can be used to recall information in a redintegrative process—e.g., given the cue-word (*tree*), an individual may not directly remember the response-word (*rock*) but may remember some other aspect of the elaboration that leads to activation of the whole

memory. The example of imagery given above is richly elaborated and, as long as other semantically similar words (e.g., river and/or grass) are not present in the to-be-learned material, likely distinct; the example of sentence generation is not very elaborate but the phrase “petrified tree” is meaningful (i.e., not arbitrary) and distinct. As noted above, both of these elaborative strategies are effective though it appears that imagery is best when highly imageable words are used, otherwise, imagery and verbal mediation appear to be equally effective (Richardson, 1998).

Among the less effective encoding strategies are passive reading and rote rehearsal. Using a passive reading strategy, one simply reads the words as they are presented; in rote rehearsal, one intentionally repeats to-be-learned material for as many repetitions as possible. With passive reading, it seems likely that after directing one’s attention to the to-be-learned material, one is at the mercy of automatic processes (e.g., priming, Hebbian learning). With regards to rote rehearsal, in theory, each repetition strengthens the newly formed memory trace (Atkinson & Shiffrin, 1968), however, this does not appear to be the case, as neither the number of repetitions nor the duration that one maintains an item in mind appear to affect recall (Bradley & Glenberg, 1983; Craik & Watkins, 1973)¹. Still, the available evidence suggests that rote rehearsal is superior to passive reading (e.g., Bailey et al., 2008).

In practice, researchers often group various strategies as presented above (i.e., imagery and sentence generation vs. rote and passive reading) and label them as effective and ineffective or as elaborative and non-elaborative strategies, respectively (e.g., Bailey et al., 2008; Richardson, 1998; Unsworth, 2016). We favor the later, as these terms suggest something about the underlying cognitive processes. In our view (see also Martinez & Singleton, 2019; Tirre, 1991), elaboration is a verbal inductive process—one selects relevant features and attempts to induce relationships (e.g., *how are a rock and a tree similar?* They both can be found in a forest). As an inductive process, elaborative rehearsal

¹ There is evidence that repetition facilitates second language learning (Ghazi-Saidi & Ansaldo, 2017; Majerus, 2013; Nishiyama & Ukita, 2013), thus the lack of an effect of repetition may only apply to associative learning paradigms using familiar words.

should rely on a number of abilities (e.g., processing speed, verbal ability/crystallized intelligence), particularly fluid intelligence, as fluid intelligence is defined as our ability to perceive novel relations (Cattell, 1943) and is profitably operationalized via inductive reasoning tasks (Marshalek et al., 1983; Wilhelm, 2005). In addition to our theoretical rationale for highlighting the role of fluid intelligence, we also chose to investigate the relationship between paired-associate performance and fluid intelligence because there have been a number of individual differences studies linking fluid intelligence and one's ability to encode information into declarative long-term memory (e.g., Kaufman et al., 2009; Mogle et al., 2008).

Regarding non-elaborative strategies, this class of strategies also likely depends on a number of cognitive abilities, particularly working memory capacity or our ability to maintain relevant information in mind and ignore irrelevant information (Engle, 2018; Oberauer, 2019). Working memory capacity is typically operationalized via immediate memory tasks that impede rehearsal strategies and/or increase interference (Cowan, 2008; Oberauer et al., 2012), such as complex span tasks (Daneman & Carpenter, 1980). Individuals with greater working memory capacity are better able to focus attention on items and avoid interference from internal and external distractors, thus increasing the likelihood that relevant information will be retrieved at a later point in time (Unsworth et al., 2011; Unsworth, Brewer, & Spillers, 2013; Unsworth, Spillers, & Brewer, 2012).

To recapitulate, according to our view, one should see stronger relations between fluid intelligence and paired-associate learning when individuals engage in elaborative rehearsal to encode information; on the other hand, one should see stronger relations between paired-associate learning and working memory capacity when information was encoded using non-elaborative strategies. While fluid intelligence and working memory capacity are highly correlated at the latent variable level, they are not isomorphic and, at the observed variable level, correlations between indicators of these constructs are often moderate and rarely exceed 0.5 (Ackerman et al., 2005). Thus it should be possible to see evidence of differential relations.

The present study

To investigate how strategy-use may affect the abilities assessed by paired-associate tasks, we chose to use archival data. As is fairly typical (in our experience) of individual differences research using paired-associate tasks, none of the data sets we acquired included information about strategy-use nor was there any evidence that participants were explicitly instructed to use one or another strategy. Thus, our approach was to 1) infer strategy-use based on distributional and latent class analyses (described below); 2) use the results of the latent class analyses to group individuals based on inferred strategy-use; 3) perform regression analyses within each group identified in the data sets; 4) finally, because there appears to be a relationship between individuals' propensity to use elaborative strategies and other cognitive abilities (Hertzog et al., 2007; Unsworth, 2016), we offer further evidence of the validity of our methods by examining relationships between group membership and our predictors. We now elaborate on our rationale.

As stated above, there is clear evidence that performance differs as a result of strategy-use, with elaborative encoding resulting in better performance compared to non-elaborative rehearsal (Bower & Winzenz, 1969; Shaughnessy, 1981). If participants show a preference for one *or* another strategy-type, then paired-associate performance should be multimodal. Specifically, we predicted that performance would be bimodal, with individuals favoring elaborative strategies tending to outperform individuals favoring non-elaborative strategies.

The assumption that individuals favor a specific encoding strategy or strategy-type is critical to our investigation. While there is research suggesting that individuals employ a variety of strategies within a single task (Bailey et al., 2008; Unsworth, 2016), there is reason to believe that individuals may favor some strategies over others (i.e., individuals may use a variety of strategies but a greater proportion will be of one class or another). First, many believe elaborative and non-elaborative strategies are just as effective (Dunlosky & Hertzog, 2000; Shaughnessy, 1981), thus absent any knowledge about the effectiveness of elaborative strategies, one's proclivity to use particular strategies is likely guided by other

factors such as motivation or ability. In fact, there is evidence indicating that abilities such as working memory capacity are related to elaborative strategy-use, with higher-ability individuals more likely to report using elaborative encoding (Hertzog et al., 2007; Unsworth, 2016). Second, there is evidence indicating that when given a choice of what strategy to use and experience with various strategies, individuals fail to update their strategy usage, suggesting a preference (Shaughnessy, 1981). Third, in individual differences research, and in the data sets examined here, paired-associate tasks consists of a relatively small number of trials and feedback is rarely offered, thus opportunities for individuals to try different strategies and adapt are minimal. Lastly, it should be pointed out that the idea of classifying individuals as elaborators and non-elaborators is not novel (e.g., Pressley & Levin, 1977). Taken together, it seems plausible that individuals approach a paired-associate task with a particular strategy in mind and this choice is guided by their prior knowledge, level of motivation, ability, and other factors.

While we expect to observe evidence of two groups in the distributions of performance, it is difficult to classify *individuals* as elaborators or non-elaborators based on which distribution they fall in, as score distributions likely overlap. Moreover, an individual may use an elaborative strategy but perform poorly due to ability or one may use a rote strategy and perform exceptionally well. In order to classify individuals on an unobserved variable, we chose to conduct latent class analyses (McCutcheon, 1987; Oberski, 2016). A latent class analysis is similar to a factor analysis in that one is attempting to identify patterns amongst several observed variables, however, in a latent class analysis, the latent variable is discrete rather than continuous—in this case, whether individuals favored elaborative or non-elaborative strategies. In latent class analyses, the observed variables are also discrete—in this case, binary (right/wrong) *item responses*. Aside from overall differences in performance, one would also expect to see different item response *patterns* as a result of using different strategies. For example, individuals favoring elaborative rehearsal may be more likely to recall items A, D, and F but not B and C, while those using a rote-rehearsal strategy may exhibit a different pattern. It is beyond the scope of the present study to investigate the item characteristics that result in different item response patterns in paired-associate

learning but the reader may be interested to know that there are methods to investigate this question (Embretson, 1984, 1992; Embretson & Daniel, 2008).

Once individuals are grouped into classes based on strategy then regression analyses can be conducted within classes and results compared across them. We predicted that in individuals classified as favoring an elaborative strategy, fluid intelligence would be the strongest predictor of paired-associate learning; in individuals classified as having used non-elaborative strategies, working memory capacity would be the strongest predictor.

Finally, as further evidence of the validity of our approach, we investigated group differences in our predictors. Using questionnaires, the literature indicates that there is a modest but reliable association between strategy-use and cognitive abilities such as working memory capacity (Dunlosky & Hertzog, 1998; Hertzog et al., 2007; Unsworth, 2016). There are a number of possible reasons for this relationship. One possibility is that individuals who are more likely to apply elaborative strategies in paired-associate learning tasks are also more likely to apply similar strategies in other cognitive tasks and benefit from them (Bailey et al., 2008; cf. Bartsch et al., 2018). In a similar vein, elaborative strategies are effortful (Hasher & Zacks, 1979; Kee, 1994) thus motivation may come into play: those individuals who are highly motivated to perform well will tend use elaborative rehearsal during associative learning and also try their best in other tasks; those who are less motivated will tend use non-elaborative strategies and also put less effort in other tasks. The fact that elaborative strategies are effortful leads to another possibility *if* one takes a resource-based view of attention (Kahneman, 1973): those individuals who have greater resources available to devote to the more cognitively demanding activity of elaboration will be able to employ the most effective strategies and also do well in other attention demanding tasks. Regardless of the reason for the relationship, we expected our indicators of working memory capacity and fluid intelligence to exhibit relationships similar to what has been observed when questionnaires are used to identify strategy-use.

Methods

All analyses (described above) were conducted using archival data. Our aim was to acquire data sets that included data from at least 200 participants who completed at least one measure of verbal paired-associate learning, fluid intelligence, and working memory capacity. The sample size of 200 took into consideration that 1) we expected to find evidence of two groups and 2) we would be splitting samples into subgroups based on strategy-use and so we wanted at least one of the groups to be large enough to reliably identify a moderate effect—with a sample size of 100 and alpha and power of .05 and .80, respectively, we can reliably detect an r of about 0.3 (or R^2 of about 0.09). While we understood that it was possible for a subgroup to be quite small, we reasoned that we would still be able to investigate patterns across data sets and in this way strengthen our conclusions.

There were eight data sets we identified for inclusion, however, we were only able to acquire four. The four data sets we were able to acquire (in order of acquisition) have been described in O'Rourke et al (2019); Jackson, Hughes, and Doughty (2013); Wilhelm, Hildebrandt, & Oberauer (2013) and Ellis, Robinson, and Brewer (2019). Here we provide only the most relevant details; additionally, we provide descriptives and correlations in the Appendix and analysis scripts and data can be found at <https://osf.io/8cwb2>.

The data sets

O'Rourke et al. (2019). The first data set we acquired came directly from our laboratory. O'Rourke et al. (2019) investigated the effects of transcutaneous vagal nerve stimulation on grammar and vocabulary learning over three days. A battery of cognitive tasks were administered one day prior to and one day after nerve stimulation. The battery administered prior to nerve stimulation included paired-associate learning, a verbal inductive reasoning measure indexing fluid intelligence, and a complex span task indexing working memory capacity. For experimental purposes, there were two versions of each of the tasks however O'Rourke and colleagues reported that the tasks were equivalent, thus, in most cases,

the data was collapsed except when submitting paired-associate responses to the latent class analysis—in that case, it would be inappropriate to collapse data. The data set included data from 206 individuals.

The paired-associate task was modified from Doughty et al. (2007). There were three consecutive study trials and one test. Pairs were presented pseudo-randomly across all study trials and the test trial. During study trials, pairs appeared on screen for 3 s each. At test, participants were provided with the nonwords and were given an unlimited amount of time to type the associated English word. Participants were never given feedback.

The fluid intelligence measure used by O'Rourke and colleagues was letter sets (based on Ekstrom et al., 1976). Letter set items consisted of five sets of letters. Four of the sets obey a particular rule and one of the sets does not. The participant must identify the set that does not follow the same rule as the others.

The remember-and-count task (Hughes et al., 2016) is a complex-span task consisting of a visuospatial memory task—remembering triangles of various colors and orientations—and a secondary processing component in which individuals must identify and count the number of circles in an array of circles and triangles.

Jackson, Hughes, and Doughty (2013). Jackson, Hughes, and Doughty (2013) investigated the extent to which the Hi-LAB, a language aptitude battery, provided incremental validity over fluid intelligence measures. The data set included a paired-associate task, three measures of fluid intelligence, and two measures of working memory capacity. Because fluid intelligence and working memory capacity are theorized to be domain-general and because we had access to a number of indicators per predictor, we decided to form composites by summing standardized scores (i.e., z-scores).

The data set included data from 269 individuals however we did not have paired-associate data for 20 individuals and an additional 34 individuals were missing data for one of the other variables—ultimately, we had complete data from 215 individuals.

The paired-associate task was similar to the task used by O'Rourke et al., 2019, however, there was a single version. The fluid intelligence measures were letter sets, number series (Thurstone, 1938), and matrix reasoning—all inductive reasoning tasks.

The tasks used as indicators of working memory were running memory span (Bunting et al., 2006) and a nonword span (Linck et al., 2013). Although nonword span may be more appropriately viewed as measure of short-term memory span, both short-term memory span and working memory capacity are highly correlated and, in theory, rely on an ability to maintain information in mind (Colom et al., 2006; Kane et al., 2004)

This is the only data set that included outliers (z-scores greater than |3.33|)—three scores, all below the cut-off of -3.33 were replaced with scores equal to the cut-off.

Wilhelm, Hildebrandt, and Oberauer (2013). The third data set we acquired came from a study investigating whether different types of working memory capacity tasks measure the same construct. The data set included three paired-associate tasks, three fluid intelligence tasks, and 12 measures of working memory capacity.

The three-paired associate tasks differed in their content: one task consisted entirely of words, another paired numbers with words, and the third paired letters with positions in a grid. Because the focus of the present study is on verbal paired-associate tasks, we only analyzed the word-word version. The paired-associate task consisted of two study-test blocks with each block using different lists of 20 pairs for a total of 40 pairs. During the study block, pairs were presented on-screen for 4 s; during the test block, participants were presented with one half of a pair and given an unlimited amount of time to type in the associated item. Between study and test blocks, participants completed another task for approximately 3 min, thus there was a delay between study and test. Participants were never given feedback.

The fluid intelligence measures included a verbal deductive reasoning task, an arithmetic reasoning task, and figural reasoning task—as with the Jackson et al. (2013) data set, we formed composites by summing standardized scores. With regard to the working memory tasks, we chose to form a composite using three complex span tasks. We chose to do this because three of the four data sets we collected included complex span tasks and was therefore more consistent. The three complex span tasks were reading span, operation span, and rotation span (Kane et al., 2004; Unsworth et al., 2005).

The data set included data from 262 individuals however 45 individuals did not have complete paired-associate data and another two individuals were missing data for one of the predictors. In total, we had access to data from 215 participants with paired-associate data and all predictors.

Ellis, Robinson, and Brewer (2019). The final data set we used in our analyses came from Ellis, Robinson, and Brewer (2019). Ellis and colleagues investigated predictors of multiply-constrained problem solving. The data set included a paired-associate task, three measures of fluid intelligence, and four measures of working memory capacity.

The paired associate task consisted of three study-test blocks, with each block consisting of 10 different pairs for a total of 30 items. During the study portion, participants viewed pairs on-screen for 2 s each. At test, participants were given one-half of a pair and asked to type the associated word within 5 s. Participants were never given feedback.

The three fluid intelligence measures were letter sets (Ekstrom et al., 1976), number series (Thurstone, 1938), and Raven's progressive matrices (Raven et al., 1998). A fluid intelligence composite was formed using all three tasks.

The four working memory capacity tasks were reading span, operation span, rotation span, and symmetry span (Kane et al., 2004; Unsworth et al., 2005). A working memory capacity composite was formed using all four tasks.

A total of 491 individuals participated in Ellis, Robinson, and Brewer's (2019) study, however, we had paired-associate data for 437 of these participants and only about half of the participants completed at least one measure of fluid intelligence and some were also missing a working memory capacity measure. To preserve as much data as possible, for this data set, we formed composites using at least two indicators of a given construct. In all, 254 participants had paired-associate data along with estimates of fluid intelligence and working memory.

Data analyses

Distributional analyses. We investigated multimodality by inspecting score distributions in conjunction with using two measures of multimodality: Hartigan's dip test (Hartigan & Hartigan, 1985) and the bimodality coefficient (SAS Institute Inc., 2012). We expected to see at least two peaks in score distributions however, we also recognized that data is rarely normally distributed, thus we used Hartigan's dip test and the bimodality coefficient to support our visual inspection. Hartigan's dip test is a statistical test—a probability of .05 or less is considered evidence of multimodality. The bimodality coefficient is a proportion relating skew and kurtosis—a value of .555 or greater is considered evidence of bimodality. Pfister, Schwarz, Janczyk, Dale, and Freeman (2013) noted that neither the dip test nor the bimodality coefficient is perfectly sensitive and both are affected by skew and kurtosis (though Hartigan's test appears to be more robust); consequently, Pfister and colleagues suggested that one use both measures in addition to inspecting distributions by eye.

All plots were generated using *ggplot2* (Wickham & Chang, 2008) in *R* (*R Core Development Team, 2015*). Density plots were generated using *ggplot2*'s default settings; histogram binwidths were adjusted, to the extent possible, to be equal to an item for the given task (e.g., the binwidth for a task with 20 items was $1/20^{\text{th}}$). Hartigan's dip test statistic and the bimodality coefficient were calculated using the *dipTest* package (Maechler, 2004) for *R*.

Results and discussion. Results are provided in Table 1. Visually inspecting the distributions, one can see bimodality in paired-associate performance in two of the data sets (Jackson and colleagues' as well as Wilhelm and colleagues'); one of the paired-associate distributions appears platykurtic (O'Rourke and colleagues' data set), perhaps suggesting the presence of two overlapping distributions; the final data set (Ellis and colleagues') does not appear bimodal. Hartigans' dip test indicated multimodality in Jackson and colleagues' data set as well as in Wilhelm and colleagues' data set, however, the bimodality coefficient never suggested multimodality.

Table 1. Multimodality in Paired-Associate Performance

	A. O'Rourke et al. (2019)	B. Jackson et al. (2013)

$\bar{X}$ (SD)	10.17 (5.8)	11.23 (5.82)
Skew	0.03	-0.16
Kurt.	-1.08	-1.12
p_{HDS}	0.09	0.004
BC	0.527	0.547
	C. Wilhelm et al. (2014)	D. Ellis et al. (2019)

$\bar{X}$ (SD)	17.61 (10.40)	10.39 (6.43)
Skew	0.05	0.73
Kurt.	-1.05	-0.09
p_{HDS}	0.013	0.584
BC	0.516	0.529

Note. Kurt. = kurtosis; p_{HDS} = probability of Hartigans' test statistic; BC = bimodality coefficient.

Although the results of our distributional analyses do not unequivocally support bimodality in paired-associate performance, there was fairly clear evidence of bimodality in two data sets: Jackson and colleagues' and Wilhelm and colleagues'. O'Rourke and colleague's data appeared platykurtic, suggesting the presence of two overlapping distributions. The distribution of performance on the paired-associate task in Ellis and colleague's data set, however, does not appear bimodal.

Latent Class Analyses. The distributional analyses revealed *some* evidence of bimodality in paired-associate performance suggesting the presence of subgroups, with one group tending to outperform the other. While two of the data sets did not show clear evidence of bimodality, it is still possible for there to be subgroups. To further investigate the possibility of subgroups differing in encoding strategy, latent class analyses were conducted.

Latent class analyses were conducted in *R* using the *poLCA* package (Linzer & Lewis, 2011). Separate latent class analyses were conducted for each data set and, in the case of the O'Rourke and colleagues data set, for each version of the paired-associate task. For all analyses, *all* available verbal paired-associate responses were submitted for analysis. To identify the appropriate number of classes, we estimated a 1-class model and incremented by one class until we estimated a model with four classes. We then used the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) along with a pseudo R^2 entropy value to select the appropriate model (Nylund et al., 2007). The AIC and BIC are common fit indices used to adjudicate amongst models. Lower AIC and BIC values indicate better fit, however, in some cases, the improvement in fit is relatively small, and thus it is important to consider one's theory as well as the magnitude of the improvement in fit gained by increasing the number of classes (Nylund-Gibson & Choi, 2018). Entropy is a measure of classification accuracy ranging between 0 and 1—values closer to 1 indicate better classification accuracy (Celeux & Soromenho, 1996). For completeness, we also provide log likelihood.

Results and discussion. Results are presented in Tables 2-5. We interpret these results as suggestive of two latent classes. In each case, we observe a sharp decrease in AIC and BIC from the 1-class baseline

model to the 2-class model; increasing the number of classes beyond two classes either marginally improved fit or resulted in worse fit (see Figure 1 for an illustrative example).

Table 2. O'Rourke et al. (2019) latent class model fit statistics

Model	LL	AIC	BIC	Entropy
1-class A	-1362.88	2765.77	2818.27	
2-class A	-1138.03	2358.06	2465.68	0.94
3-class A	-1081.53	2287.05	2449.80	0.96
4-class A	-1060.56	2287.07	2504.94	0.97
1-class B	-1373.21	2786.43	2839.32	
2-class B	-1146.92	2375.84	2484.26	0.93
3-class B	-1095.82	2315.64	2479.59	0.96
4-class B	-1066.16	2298.33	2517.81	0.96

Note. A/B models correspond to two versions of paired-associates task given to participants. A total of 102 participants received version A; 104 participants received version B.

Table 3. Jackson et al. (2013) latent class model fit statistics

Model	LL	AIC	BIC	Entropy
1-class	-3251.42	6542.84	6613.19	
2-class	-2695.78	5473.57	5617.78	0.93
3-class	-2592.55	5309.09	5527.17	0.88
4-class	-2550.48	5266.96	5558.91	0.84

Note. N = 249

Table 4. Wilhelm et al. (2013) latent class model fit statistics

Model	LL	AIC	BIC	Entropy
1-class	-5694.59	11469.18	11604.37	
2-class	-4797.90	9757.80	10031.57	0.96
3-class	-4636.10	9516.20	9928.55	0.94
4-class	-4561.86	9449.71	10000.64	0.9

Note. N = 217

Table 5. Ellis et al. (2019) latent class model fit statistics

Model	LL	AIC	BIC	Entropy
1	-8191.28	16442.55	16564.95	
2	-7405.25	14932.50	15181.37	0.90
3	-7224.96	14633.91	15009.27	0.85
4	-7130.60	14507.21	15009.04	0.84

Note. N = 437

Figure 1. Plot of fit indexes using O'Rourke et al. (2019) data. PAT = paired-associate task; A/B correspond to the two versions of paired-associate tasks used. Lower values indicate better fit.

These analyses, in conjunction with the distributional analyses, provide evidence for two classes, which, based on our theory, we believe correspond to preference for elaborative or non-elaborative strategies. According to our view, participants use a variety of encoding strategies but favor elaborative or non-elaborative strategies due to factors such as ability, motivation, and knowledge of strategies. Elaborative and non-elaborative strategies rely on different cognitive processes and vary in effectiveness which, when implemented, result in different performance distributions and response patterns. The results of the latent class analyses along with the distributional analyses support our predictions.

Note that we do not argue that all strategies within a particular strategy-type are equivalent. Imagery and verbal mediation are two elaborative strategies that individuals may favor to different degrees and

almost certainly rely on different cognitive processes. However, the results suggest that one can parsimoniously account for differences in strategy with two classes.

Regression analyses. Our next set of analyses used the results of the latent class analyses to classify participants as either elaborators or non-elaborators and then investigated relationships between paired associate performance on the one hand and fluid intelligence and working memory capacity on the other hand, *within* classes.

In a latent class analysis, participants are assigned posterior probabilities of class membership based on their response patterns. Here, we used the results of the 2-class models and assigned participants to the class they were most likely in. We then labeled the higher performing class “elaborators” and the lower performing class “non-elaborators”. Once participants were classified, we conducted regression analyses for each data set and class. The outcome variable was paired-associate performance and the predictors were measures of fluid intelligence and working memory capacity. When possible, we used composite scores in our analyses.

As articulated in the introduction, we argue that elaborative rehearsal primarily draws on fluid intelligence, while rote rehearsal primarily draws on working memory capacity.

Results and discussion. The results of the regression analyses are presented in Tables 6-9. To the extent that our classification of individuals is accurate, the pattern of results appear to support the idea that elaborative rehearsal primarily relies on fluid intelligence while rote rehearsal primarily relies on working memory capacity.

Table 6. O'Rourke et al. (2019) regression results

Elaborative	<i>df</i>(2,105)	$R^2 = 0.03$	$Adj R^2 = 0.01$
	β	<i>SE</i>	<i>p</i>
LSET	0.10	0.10	0.323
RAC	0.11	0.10	0.289

Non-Elab	<i>df</i>(2,95)	$R^2 = 0.12$	$Adj R^2 = 0.10$
	β	<i>SE</i>	<i>p</i>
LSET	0.05	0.10	0.616
RAC	0.32	0.10	0.002 *

Note. The two versions of paired-associate tasks were collapsed. LSET = letter sets; RAC = remember-and-count.

Table 7. Jackson et al. (2013) regression results

Elaborative	<i>df</i>(2,103)	$R^2 = 0.09$	$Adj R^2 = 0.07$
	β	<i>SE</i>	<i>p</i>
Gf	0.20	0.10	0.043 *
WMC	0.17	0.10	0.096

Non-Elab	<i>df</i>(2,106)	$R^2 = 0.18$	$Adj R^2 = 0.17$
	β	<i>SE</i>	<i>p</i>
Gf	0.18	0.10	0.106
WMC	0.30	0.10	0.006 *

Note. Gf = fluid intelligence composite; WMC = working memory capacity composite

Table 8. Wilhelm et al. (2013) regression results

Elaborative	<i>df</i>(2,125)	$R^2 = 0.07$	$Adj R^2 = 0.06$
	β	<i>SE</i>	<i>p</i>
Gf	0.19	0.10	0.045 *
WMC	0.12	0.10	0.213

Non-Elab	<i>df</i>(2,84)	$R^2 = 0.21$	$Adj R^2 = 0.19$
	β	<i>SE</i>	<i>p</i>
Gf	0.15	0.11	0.206
WMC	0.36	0.11	0.002 *

Note. Gf = fluid intelligence composite; WMC = working memory capacity composite

Table 9. Ellis et al. (2019) regression results

Elaborative	<i>df</i>(1,76)	$R^2 = 0.14$	$Adj R^2 = 0.11$	
	β	<i>SE</i>	<i>p</i>	
Gf	.41	0.13	0.002	*
WMC	-.09	0.13	0.505	

Non-Elab	<i>df</i>(2,172)	$R^2 = 0.05$	$Adj R^2 = 0.04$	
	β	<i>SE</i>	<i>p</i>	
Gf	0.20	.08	0.008	*
WMC	0.04	.08	0.596	

Note. Gf = fluid intelligence composite; WMC = working memory capacity composite

The results of the regression analyses correspond to the results of the distributional analyses in that the clearest support for our theory came from two data sets: Jackson, Hughes, and Doughty (2013) and Wilhelm, Hildebrandt, and Oberauer (2013). These two data sets also happen to be the data sets in which paired-associate performance was most clearly bimodal. The results of the regression analyses using the O'Rourke et al. (2019) data set were more ambiguous and it is in this data set that paired-associate performance was platykurtic, suggesting a mixture of two distributions but not clearly depicting it. The clearest deviation from the expected pattern of results was in the Ellis, Robinson, and Brewer (2019) data set; in this data set, paired-associate performance appeared unimodal though somewhat skewed. It is possible that the results of the distributional analyses and the regression analyses reflect how *strongly* individuals in these samples preferred one or another strategy—the stronger the preference, the clearer the results.

Relationship between class membership and abilities. Prior research has found that cognitive abilities are related to strategy-use in paired associate performance, with higher ability individuals tending to report using elaborative strategies more frequently than lower ability individuals (Hertzog et al., 2007; Unsworth, 2016). If our classification of individuals into elaborators and non-elaborators is tenable, then we too should observe a modest correlation between strategy-use and ability. To investigate this, we correlated class membership with fluid intelligence and working memory capacity (this is equivalent to

conducting independent group *t*-tests and calculating Cohen's *d*, however it provides us with *r* as an effect size estimate). The data used here were exactly the same as those used in the regression analyses.

Results and discussion. The results are displayed in Table 13. These results are in agreement with others who have used questionnaires to investigate strategy-use and ability correlations. Unsworth (2016) reported a correlation between self-reported elaborative strategy-use and working memory capacity of 0.31. Hertzog, Dunlosky, and Robinson (2007) also examined this question with a range of cognitive abilities and reported correlations between 0.25 and 0.49. Thus, using different methods, we arrived at similar conclusions: elaborative strategy-use is correlated with cognitive abilities. These convergent results offer evidence of the validity of our approach.

Table 13. Correlation between elaborative strategy use and other abilities

	<i>r</i> _{Gf}	<i>r</i> _{WMC}	<i>N</i>
O'Rourke et al. (2019)	0.27	0.29	206
Jackson, Hughes, and Doughty (2013)	0.34	0.42	215
Wilhelm, Hildebrandt, and Oberauer (2013)	0.25	0.22	215
Ellis, Robinson, and Brewer (2019)	0.17	0.16	254

Note. All *p*-values < 0.05. Gf = fluid intelligence; WMC = working memory capacity.

General Discussion

The primary aim of this study was to investigate differential relations between paired-associate learning on the one hand and fluid intelligence and working memory capacity on the other, as a function of strategy-use. To that end, we acquired several data sets and investigated whether there was evidence of strategy-type preference by conducting distributional and latent class analyses. We then used the results of our analyses to classify individuals and conducted regression analyses within subgroups. Finally, we offered further support for our approach by investigating correlations between strategy-use and fluid intelligence and working memory capacity. Generally, we found evidence of two groups which we

labeled elaborators and non-elaborators. The results of our regression analyses suggest that paired-associate learning is more reliant on fluid intelligence when one utilizes elaborative rehearsal and more reliant on working memory capacity when one utilizes non-elaborative strategies. In accord with prior research (Hertzog et al., 2007; Unsworth, 2016) we also found that higher-ability individuals were more likely to engage in elaborative rehearsal.

That the cognitive processes assessed by verbal paired-associate tasks may vary as a function of strategy-use should be a concern for all researchers and practitioners who use such tasks. From a theoretical perspective, reliable and valid assessments are critical to theory development. As Hintzman (2011) noted in reference to another memory paradigm (free recall), failing to account for strategy use “creates a nightmare for the theorist who wants to understand what is really going on...one should avoid averaging over strategies because the processes either are different or are deployed in different ways (p., 255).” From a practical perspective, verbal paired-associate tasks are included in neuropsychological batteries such as the Wechsler Adult Intelligence Scales (Wechsler, 1997a) and the Wechsler Memory Scale (Wechsler, 1997b)—two of the most popular batteries used by clinicians to assess intelligence and memory functioning, respectively (Camara et al., 2000). To our knowledge, neither of these batteries provide information on the use of strategies or their effect on the validity of verbal paired-associate tasks. Paired-associate tasks are also used in language aptitude batteries but, to our knowledge, batteries such as the Modern Language Aptitude Test (Carroll & Sapon, 1959) do not direct individuals to use one or another strategy. It may be that knowledge of strategies and the decision to use elaborative strategies contributes to the predictive validity of paired-associate tasks in language aptitude batteries but it is also possible that differences in strategy-use result in greater measurement error.

Limitations. We wish to point out some limitations. First, we inferred strategy-use using statistical methods but we may be capturing some other source of variance in paired-associates performance. For example, a reviewer pointed out that our analyses may have simply captured differences between high and low paired-associate performers and therefore the labels “elaborators” and

“non-elaborators” may be mistaken. Indeed, those individuals we labeled as elaborators tended to outperform the non-elaborators (see the appendix for descriptives), however, as pointed out in the introduction, strategy-use and paired-associate performance are intimately tied. Moreover, it is difficult to explain our pattern of results without recourse to differences in cognitive processing; we suggest these differences are due to differences in encoding strategies however the differences may have arisen due to some other difference in cognitive processing. While other researchers have made similar conclusions based on the distribution of data across a sample (e.g., O’Rourke & Colflesh, 2015; Tanner & Van Hell, 2014) additional research is required to determine if our inference is correct and/or if yet to be determined sources of variability play a role. Second, our method of classifying individuals and then examining relations within groups may not produce the most accurate results (Bolck et al., 2004; Vermunt, 2010). For example, we grouped people into two classes but we note that it is unlikely that participants exclusively used one strategy or strategy-type. Lastly, we did not include other relevant predictors. It is possible that the effects we observed are actually mediated by some other cognitive variable such as processing speed or verbal ability.

Future Directions. Future research should continue to investigate the validity of the classification scheme used here and the methods used to classify individuals. While our results are in accord with prior work (e.g., Tirre, 1991) and the theory that elaborative strategies are verbal inductive processes while non-elaborative strategies largely rely on the ability to maintain attention on target information (i.e., working memory capacity), these results should be replicated and expanded on. With regard to replication, it should be relatively easy to acquire other data sets and reanalyze them, however, it may be more informative if a data set that also included a post-assessment strategy questionnaire were analyzed; in this way, one would be able to cross-check the results of a latent class analysis with the questionnaire data. Of course, another option is to experimentally manipulate strategy-use by instructing and explicitly asking participants to use a particular strategy or strategy-type and then investigate relations with other variables.

With regard to expanding on the present work, there are a number of variables that should be investigated—we suggest only a few. First, we investigated strategy-use in verbal paired-associate tasks, however, the results should be similar if other memory paradigms using verbal stimuli are used, particularly those involving long-term memory encoding and retrieval, such as free recall of 10 or more items. Second, we only investigated effects of fluid intelligence and working memory capacity but other variables such as general knowledge and processing speed are predictive of paired-associate learning (Dunlosky & Hertzog, 1998; Kyllonen et al., 1991; Salthouse, 1994) and should be examined. Third, motivation is very likely a factor in one's decision to use elaborative or non-elaborative strategies—those who are least motivated will likely choose less cognitively demanding strategies such as passive reading or rote rehearsal. Finally, one should also investigate task characteristics and how they affect results. In the present study, the distribution of paired-associate scores in the Ellis, Robinson, and Brewer (2019) study were positively skewed and apparently unimodal and it is in this data set that the results of our regression analyses most deviated from what was expected. One possibility is that greater fluid intelligence is needed as the learning task gets harder. Another possibility is that the characteristics that made the task difficult also increased reliance on fluid intelligence. For example, Ellis, Robinson, and Brewer presented stimuli for 2 seconds while others used longer presentation intervals. It also appears that the paired-associate task in Ellis, Robinson, and Brewer (2019) used a combination of related (e.g., flame-hose) and unrelated (e.g., pen-glass) word pairs within a list and some word pairs appeared related across lists as well, either semantically or phonetically (e.g., *pen* appeared in one list and *hen* in another). The ability to mitigate interference may be related to fluid intelligence (Bunting, 2006; Shipstead et al., 2016) and this may be the reason this data set did not yield the expected results. Further research, as suggested above, should result in better estimates and elaborate on the theory presented here.

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APPENDIX:
Descriptives and Correlations

O'Rourke et al. (2019)

Table A1. Descriptives for data derived from O'Rourke et al. (2009) data set

Variable	Group	Mean	SD	Skew	Kurtosis
PAT	Whole	10.17	5.8	0.03	-1.08
	Elab.	14.82	3.29	0.1	-1.2
	Non-Elab.	5.05	2.95	-1.12	0.3
RAC	Whole	0.52	0.18	-0.14	-0.1
	Active	0.57	0.17	-0.04	-0.4
	Passive	0.47	0.19	-0.08	0.02
LSET	Whole	11.54	1.99	-0.82	0.05
	Active	12.06	1.63	-0.81	0.29
	Passive	10.99	2.2	-0.63	0.22

Note. $N_{\text{whole}} = 206$; $n_{\text{elab}} = 108$; $n_{\text{non-elab}} = 98$

Table A2. Correlations for data derived from O'Rourke et al. (2009) data set

	PAT	RAC
<u>whole group</u>		
RAC	0.36	
LSET	0.30	0.40
<u>Elab</u>		
RAC	0.15	
LSET	0.14	0.38
<u>Non-elab</u>		
RAC	0.32	

LSET	0.15	0.32
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Note. Correlations in bold, $p < 0.05$

Jackson et al. (2013)

Table A3. Descriptives for data derived from Jackson et al. (2013)

Variable	Group	Mean	SD	Skew	Kurtosis
PAT					
	Whole	11.23	5.82	-0.16	-1.12
	Elab.	16.30	2.62	-0.19	-1.31
	Non-elab.	6.29	3.25	-0.34	-0.97
RMS					
	Whole	2.99	0.75	-0.34	1.34
	Elab.	3.10	0.63	0.13	0.67
	Non-elab.	2.88	0.85	-0.36	0.93
NWS					
	Whole	170.01	22.31	-0.98	0.64
	Elab.	179.50	16.32	-0.72	0.14
	Non-elab.	160.77	23.52	-0.82	-0.22
LSET					
	Whole	11.19	2.83	-1.24	1.25
	Elab.	12.23	1.92	-1.14	0.69
	Non-elab.	10.19	3.20	-0.87	0.08
NumSeries					
	Whole	6.33	1.90	0.10	-0.63
	Elab.	6.71	1.89	-0.04	-0.97
	Non-elab.	5.96	1.85	0.23	-0.20
MR					
	Whole	6.94	1.35	-0.38	0.04
	Elab.	7.11	1.30	-0.34	-0.43
	Non-elab.	6.76	1.38	-0.40	0.28

Note. $N_{\text{whole}} = 215$; $n_{\text{elab}} = 106$; $n_{\text{non-elab}} = 109$

Table A4. Correlations for data derived from Jackson et al. (2013) data set

	PAT	NWS	RMS	LSET	NumSeries
<u>whole group</u>					
NWS	0.52				
RMS	0.23	0.33			
LSET	0.47	0.60	0.49		
NumSeries	0.27	0.31	0.20	0.39	
MR	0.19	0.16	0.19	0.29	0.32
<u>Elaborators</u>					
NWS	0.24				
RMS	0.10	0.18			
LSET	0.26	0.38	0.33		
NumSeries	0.17	0.14	0.14	0.28	
MR	0.11	-0.04	0.07	0.17	0.25
<u>Non-Elaborators</u>					
NWS	0.41				
RMS	0.26	0.36			
LSET	0.37	0.59	0.54		
NumSeries	0.23	0.35	0.20	0.41	
MR	0.18	0.21	0.25	0.32	0.34

Note. Correlations in bold, $p < 0.05$

Wilhelm et al. (2013)

Table A5. Descriptives for data derived from Wilhelm et al. (2013)

Variable	Group	Mean	SD	Skew	Kurtosis
PAT					
	Whole	0.44	0.26	0.05	-1.05
	Elab.	0.62	0.15	0.41	-0.64
	Non-elab.	0.17	0.10	0.04	-0.89
readSpan					
	Whole	0.84	0.13	-0.95	0.66
	Elab.	0.85	0.11	-0.76	0.28
	Non-elab.	0.81	0.14	-0.91	0.18
Ospan					
	Whole	0.91	0.07	-0.96	0.18
	Elab.	0.93	0.06	-1.30	1.30
	Non-elab.	0.89	0.07	-0.55	-0.60
RoSpan					
	Whole	0.71	0.16	-0.60	-0.17
	Elab.	0.73	0.14	-0.45	-0.53
	Non-elab.	0.67	0.18	-0.48	-0.55
Verbal Gf					
	Whole	0.54	0.16	-0.25	-0.29
	Elab.	0.57	0.14	-0.13	-0.32
	Non-elab.	0.50	0.17	-0.20	-0.60
Numerical Gf					
	Whole	0.52	0.17	0.04	-0.51
	Elab.	0.55	0.16	0.02	-0.71
	Non-elab.	0.48	0.18	0.22	-0.35
Figural Gf					
	Whole	0.44	0.17	0.02	-0.22
	Elab.	0.47	0.16	0.04	-0.05
	Non-elab.	0.40	0.17	0.04	-0.55

Note. $N_{\text{whole}} = 215$; $n_{\text{elab}} = 119$; $n_{\text{non-elab}} = 87$

Tabl A6. Correlations data for derived from Wilhelm et al. (2013)

	PAT	ReadSpan	Ospan	RoSpan	Verbal Gf	Num Gf
Whole Group						
ReadSpan	0.24					
Ospan	0.29	0.59				
RoSpan	0.29	0.41	0.36			
verbal Gf	0.28	0.29	0.38	0.46		
Num Gf	0.23	0.19	0.30	0.41	0.54	
Fig Gf	0.33	0.24	0.27	0.40	0.41	0.46
Elaborators						
ReadSpan	0.19					
Ospan	0.09	0.55				
RoSpan	0.19	0.33	0.25			
verbal Gf	0.17	0.28	0.38	0.36		
Num Gf	0.08	0.15	0.20	0.30	0.45	
Fig Gf	0.32	0.16	0.22	0.28	0.35	0.38
Non-Elaborators						
ReadSpan	0.26					
Ospan	0.35	0.61				
RoSpan	0.45	0.46	0.42			
verbal Gf	0.34	0.26	0.31	0.52		
Num Gf	0.19	0.17	0.34	0.48	0.59	
Fig Gf	0.28	0.27	0.24	0.50	0.42	0.51

Note. Correlations in bold, $p < 0.05$

Ellis et al. (2019)

Table A7. Descriptives for data derived from Ellis et al. (2019)

Variable	Group	Mean	SD	Skew	Kurtosis
PAT					
	Whole	0.35	0.21	0.73	-0.09
	Elab.	0.61	0.15	0.47	-0.68
	Non-elab.	0.23	0.11	-0.10	-0.79
readSpan					
	Whole	54.67	11.39	-0.59	-0.10
	Elab.	57.34	10.01	-0.65	-0.18
	Non-elab.	53.46	11.79	-0.52	-0.21
Ospan					
	Whole	56.35	14.89	-1.39	1.67
	Elab.	58.08	14.18	-1.48	2.40
	Non-elab.	55.58	15.16	-1.34	1.36
symSpan					
	Whole	26.06	8.85	-0.51	-0.41
	Elab.	27.14	8.46	-0.47	-0.26
	Non-elab.	25.58	9.00	-0.51	-0.52
RoSpan					
	Whole	34.64	13.45	0.03	-0.69
	Elab.	37.41	13.70	0.03	-0.60
	Non-elab.	33.39	13.18	0.00	-0.83
LSET					
	Whole	0.51	0.16	-0.08	-0.56
	Elab.	0.54	0.16	-0.06	-0.78
	Non-elab.	0.49	0.16	-0.07	-0.54
NumSeries					
	Whole	0.60	0.19	-0.26	-0.40
	Elab.	0.67	0.18	-0.36	-0.79
	Non-elab.	0.57	0.19	-0.20	-0.29
Ravens					
	Whole	0.47	0.18	-0.05	-0.38
	Elab.	0.49	0.18	-0.42	-0.49

Non-elab.	0.45	0.18	0.11	-0.21
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Note. $N_{\text{whole}} = 254$; $n_{\text{elab}} = 79$; $n_{\text{non-elab}} = 175$

Tabl A8. Correlations for data derived from Ellis et al. (2019)

	PAT	ReadSpan	Ospan	RoSpan	SymSpan	LSET	NumSeries
Whole Group							
ReadSpan	0.18						
Ospan	0.12	0.47					
RoSpan	0.18	0.32	0.41				
SymSpan	0.08	0.18	0.44	0.51			
LSET	0.23	0.19	0.21	0.22	0.18		
NumSeries	0.27	0.19	0.33	0.32	0.31	0.56	
Ravens	0.24	0.13	0.20	0.17	0.18	0.35	0.44
Elaborators							
ReadSpan	0.19						
Ospan	0.14	0.54					
RoSpan	0.14	0.35	0.50				
SymSpan	-0.03	0.19	0.45	0.39			
LSET	0.29	0.37	0.33	0.30	0.30		
NumSeries	0.07	0.48	0.45	0.51	0.27	0.41	
Ravens	0.39	0.18	0.15	0.26	0.25	0.25	0.25
Non-Elaborators							
ReadSpan	0.05						
Ospan	0.07	0.44					
RoSpan	0.10	0.29	0.36				
SymSpan	0.05	0.16	0.44	0.56			
LSET	0.18	0.10	0.15	0.15	0.11		
NumSeries	0.21	0.05	0.27	0.21	0.30	0.60	
Ravens	0.21	0.09	0.21	0.11	0.14	0.38	0.51

Note. Correlations in bold, $p < 0.05$