Contributions of associative learning to age and individual differences in fluid intelligence

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Abstract
According to the cognitive cascade hypothesis, age-related slowing results in decreased working memory, which in turn affects higher-order cognition. Because recent studies show complex associative learning correlates highly with fluid intelligence, the present study examined the role of complex associative learning in cognitive cascade models of data from adults aged 30–80 years. Path analyses revealed that an extended cascade model, in which associative learning mediated the relation between working memory and fluid intelligence, provided an adequate fit to the data. Moreover, an alternative extended cascade model, one with an additional path from speed to fluid intelligence and separate learning and secondary memory components, provided an excellent fit. These findings establish a role for complex associative learning in the extended cognitive cascade underlying age and individual differences in fluid intelligence.

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1. Introduction

Age-related changes in fluid intelligence (gF) are hypothesized to be the result of a cognitive cascade in which changes in processing speed lead to changes in working memory, which then result in changes in higher-order cognitive function (Kail & Salthouse, 1994). In children, developmental gains in processing speed are associated with increased working memory and improvements in reasoning and problem solving (Fry & Hale, 1996; Kail & Hall, 1999), whereas in adults, age-related slowing is associated with decreased working memory and a decline in reasoning ability (Gregory, Nettlebeck, Howard, & Wilson, 2009; Salthouse, 1996). However, despite considerable research, it is still not completely clear why age and individual differences in working memory are associated with differences in higher-order cognitive abilities, particularly reasoning and gF.

2. Working memory and fluid intelligence

Various hypotheses have been proposed to explain the relation between working memory task and gF. For example, Carpenter, Just, and Shell (1990) pointed out that the more difficult problems on the Raven’s Advanced Progressive Matrices (RAPM), sometimes referred to as the “gold standard” of fluid intelligence tests, typically involve more rules. They argued that individuals with greater working memory do better on the RAPM because problems with more rules place a greater load on working memory. However, recent work has not supported this hypothesis. Unsworth and Engle found that the correlation between young adults’ working memory and gF not only remained fairly constant as the number of rules that needed to be held in memory increased (Unsworth & Engle, 2005), it also remained fairly constant as the number
of items to be remembered on the working memory task increased (Unsworth & Engle, 2006). Salthouse and Pink (2008) replicated the latter finding in a cross-sectional study of adults (ages 18–98 years). Thus, working memory predicts performance on both easy and hard RAPM problems about equally well, and gF predicts performance on easy and hard working memory trials about equally well. Taken together, these findings suggest that, the amount of simultaneous storage and processing required, although important, is not critical to the correlation between working memory and gF.

A second hypothesis regarding the relation between working memory and gF involves the ability to control attention. Engle, Tuholski, Laughlin, and Conway (1999) reported that short-term memory tasks, which primarily tap storage ability, were poor predictors of gF, whereas working memory tasks, which require coordinating storage and processing operations and thus are presumed to tap controlled attention, were much better predictors. Engle et al. concluded that the ability to control attention in the presence of distraction or interference is responsible for the relation between working memory and gF. Subsequently, however, Unsworth and Engle (2006, 2007) found that although recall of short series of items on short-term memory tasks are poorly correlated with gF, recall of longer series is as highly correlated with fluid intelligence as recall on working memory tasks. Indeed, Colom and his colleagues have long argued that basic short-term storage abilities are sufficient to account for the relation between working memory and intelligence, presenting reanalyses of key data sets as well as original data to make this point (Colom, Abad, Quiroga, Shih, & Flores-Mendoza, 2008; Colom, Rebollo, Abad, & Shih, 2006).

Thus, the controlled attention hypothesis, at least as originally proposed, does not appear to provide an adequate explanation for the relation between working memory and gF. Recently, Unsworth and Engle (2007) have supplemented the controlled attention account by suggesting that working memory performance relies on the ability to use controlled attention to retrieve information from secondary memory as well as to simultaneously store and process information, implying that the storage and retrieval aspects of working memory tasks may both be important for explaining the relation between working memory and gF.

Unsworth and Engle’s (2007) new dual-component model is motivated, in part, by results showing that when the number of items to be remembered exceeds the capacity of primary memory, or what Cowan (2001) has called the focus of attention, simple working memory tasks (e.g., digit span) correlate as well with gF as complex span tasks (e.g., operation span). Unsworth and Engle hypothesized that this is because under such conditions, simple span tasks require retrieval from secondary memory, just as complex span tasks do, although in the latter case it is because the secondary processing task displaces items from primary memory. Further, Unsworth and Engle’s hypothesis is supported by recent studies showing correlations between secondary memory and reasoning ability in both children and adults (DeAlwis, Myerson, Hershey, & Hale, 2009; Mogle, Lovett, Stawski, & Slwiski, 2008). Other studies, however, suggest that working memory tasks continue to predict unique variance in gF even after controlling for the ability to retrieve information from secondary memory (Shelton, Elliot, Matthews, Hill, & Gouvier, 2010; Unsworth, Brewer, & Spillers, 2009). Thus, retrieval from secondary memory appears to explain part of the relation between working memory and gF but not all of it.

3. Learning and fluid intelligence

Successful retrieval of information from secondary memory depends not just on retrieval ability, but also on how well information is encoded and/or learned to begin with. Moreover, performance on both working memory and fluid intelligence tests depend on the ability to retrieve (the ability to retrieve to-be-remembered items in the case of working memory tasks, and the ability to retrieve rules in the case of gF tasks), with better encoding and/or learning leading to better performance. Therefore, the current study focuses on age and individual differences in learning and how they relate to differences in working memory and gF.

Working memory and performance on laboratory learning tasks are correlated in young adults (Kaufman, De Young, Gray, Brown, & Mackintosh, 2009; Tamez, Myerson, & Hale, 2008), and recent evidence suggests that working memory and learning may be correlated in older adults as well. Kirasic, Allen, Dobson, and Binder (1996) studied adults aged 18–87, and not surprisingly, they found that age was negatively correlated with processing speed, working memory, and learning. Importantly, they also found a strong positive correlation between working memory and learning. Further, path analysis revealed that age-related slowing negatively affected working memory performance, which in turn predicted differences in learning ability, but there was no direct effect of either age or speed on learning after accounting for the effect of working memory, suggesting that working memory mediates their effects on learning.

Shelton et al. (2010) suggested that the reason that working memory tasks predict how well individuals learn is because they provide retrieval practice, and retrieval practice benefits learning (Karpicke & Roediger, 2008). This suggestion was based on McCabe’s (2008) finding that items from complex span tasks are recalled better after a delay than items from simple span tasks. McCabe argued that participants repeatedly retrieve items from secondary memory on complex span tasks, but not on simple span tasks, and that this covert retrieval practice leads to better learning of complex span memory items (see also Rose, Myerson, Roediger, & Hale, 2010). Applying this idea to individual differences, Shelton et al. suggested that the better individuals are at covert retrieval, the larger their working memory spans will be, and the better they will be at learning. This idea may be extended to age differences: If older adults are poorer at covert retrieval, then their working memory spans will be smaller and they will poorer at learning.

Several recent studies have reported correlations between learning ability and gF (Kaufman et al., 2009; Tamez et al., 2008; Williams & Pearlberg, 2006). For example, Williams and Pearlberg found that three-term contingency learning, a form of complex associative learning, was strongly correlated with gF ($r \approx .50$), and Tamez et al. and Kaufman et al. reported similar results. Taken together, these findings indicate that in young adults, at least, associative learning is
a powerful predictor of individual differences in gF. Jensen (1989) has suggested that the reason learning and intelligence are related is that they both reflect the efficiency of working memory. More specifically, Verguts and De Boeck (2002a) suggested that because fluid intelligence tests involve learning different rules that must be stored and used across problems, high-performing individuals will be those who are better able to retain successful rules from previous problems. Verguts and De Boeck posited that such individuals have greater working memory, which is to suggest that individuals with greater working memory are more effective learners, and consequently better problem solvers.

Verguts and De Boeck’s (2002a) hypothesis is quite different from hypotheses that focus on the role of working memory in solving individual problems on fluid intelligence tests (e.g., Carpenter et al., 1990). This is because in the Verguts and De Boeck hypothesis, the focus is not on what determines the ability to solve one separate problem, but rather on what determines the ability to solve a whole series of inter-related problems. If the predictive ability of working memory depends not just on the use of working memory to solve the current problem, but also reflects the role of working memory in learning the rules on previous problems, then it follows that learning should at least partially mediate the relation between working memory and gF. Moreover, it raises the possibility of an extended cognitive cascade in which age-related changes in working memory affect learning ability, which, in turn, affects performance on fluid intelligence tests.

Although the original cognitive cascade models (Fry & Hale, 1996; Kail & Salthouse, 1994) focused on the determinants of age and individual differences in gF, a similar mechanism may underlie age and individual differences in learning. According to Kirasic et al. (1996), age negatively affects adults’ processing speed, and the resultant slowing is associated with decreased working memory, which, in turn, leads to declines in learning ability. According to Verguts and De Boeck (2002a) and Shelton et al. (2010), those with poorer working memory and learning ability will also perform poorly on fluid intelligence tests, which suggest that learning may mediate the relation between working memory and gF.

In order to evaluate this mediation hypothesis, we examined the fit of path analytic models of the relations among age, processing speed, working memory, complex associative learning, and gF, using multiple tasks to define each construct. In particular, we tested an extended cascade model in which age-related differences in working memory negatively impact associative learning, which, in turn, leads to decreases in gF. At issue is whether the addition of learning to the cognitive cascade can explain the relation between working memory and gF while improving the prediction of gF across the adult life span.

4. Method

4.1. Participants

Participants were recruited from a previous study of working memory across the adult lifespan (Hale et al., 2011). To obtain a sample of at least 15 participants per decade between 30 and 80 years of age whose cognitive ability would be typical for their age, recruitment was based on factor scores calculated from the complex span tasks used in the Hale et al. (2011) study. In order to preclude outliers in a sample of this size (rather than excluding them later), individuals’ factor scores were regressed on age and studentized residuals were examined. Based on this analysis, we recruited 94 participants whose studentized residuals were within ±2.0 standard deviations. The results presented here are from the 80 participants who met health and cognitive screening criteria and for whom complete data was available (see Table 1).

Participants were tested individually in two sessions lasting 2–3 h each. In session one, participants completed health and demographic questionnaires, the Shipley Vocabulary subtest, processing speed tasks, learning tasks, and fluid intelligence tests. In session two, participants completed working memory tasks as well as other tasks not relevant to this study.

4.2. Tasks and tests

4.2.1. Processing speed

In the Distance Judgment task, one central white dot appeared on the screen with a red dot to the right and a blue dot to the left. Participants were asked to decide whether the left or the right dot was closest to the central dot. In the Shape Judgment task, participants viewed a sample shape (e.g., a circle) and two choice shapes (e.g., an oval and a rectangle) that appeared side by side below the sample shape. Participants decided which of the two choice shapes was more similar to the sample shape. For each task, participants completed 10 practice trials followed by 20 test trials, and responses times were recorded in milliseconds.

4.2.2. Working memory

Participants completed three complex span tasks: Counting Span, Parallel Span, and Position Span. Counting Span

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Demographic characteristics of research participants.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group n</td>
<td>15</td>
</tr>
<tr>
<td>Age (SD)</td>
<td>34.9 (2.66)</td>
</tr>
<tr>
<td>% Female</td>
<td>60</td>
</tr>
<tr>
<td>Health (SD)</td>
<td>5.86 (0.77)</td>
</tr>
<tr>
<td>Education (SD)</td>
<td>16.7 (3.17)</td>
</tr>
<tr>
<td>Vocabulary (SD)</td>
<td>30.3 (6.81)</td>
</tr>
</tbody>
</table>
On learning trials, participants were first shown a primary word (e.g., lie) followed by the prompt, "press A." Once the participant pressed the prompted letter, the letter and the associated secondary word (e.g., fan) appeared at the bottom left-hand side of the screen. The primary word, letter prompt, and the secondary word remained on the screen until the participant pressed "enter." Next, the primary word (i.e., lie) was shown again followed by a second prompt (i.e., "press B"), and after pressing the cued letter, the letter "B" and another secondary word (e.g., rim) appeared at the bottom center of the screen until the participant pressed "enter." The third prompt (i.e., "press C") then appeared beneath the primary word. Again, the prompt disappeared once the participant pressed the cued letter, and the letter "C" and the third secondary word (e.g., day) appeared in the bottom right-hand side of the screen. This cycle was repeated until all of the six primary words with their three associated secondary words were presented. The order of presentation for the six primary words and their associated secondary words was different in each of the four learning blocks.

On test trials, the participant viewed a primary word and the first prompt ("A"), as well as a textbox located in the bottom center of the screen. The participant was asked to recall the secondary word by typing the correct word into the textbox. For example, if the participant saw the primary word lie and the prompt "A," then the correct response was to type the word fan into the textbox. Alternatively, the participant could type the letter "C" into the textbox if the secondary word could not be recalled. Participants were given feedback after each response.

Next, the participant was shown the same primary word followed by the second prompt (i.e., "B") and a textbox, and then the third prompt (i.e., "C") and a textbox. The six primary words and the prompts constituting the test block were presented in the same order as in the preceding learning block.

In the Visual Learning task, a nonverbal adaptation of the verbal learning task, the stimuli were radially symmetric patterns. Four primary cue patterns were presented, each of which was associated with three secondary patterns, and participants used a mouse click to continue rather than pressing "enter."

The procedure for the learning blocks was similar to that for the verbal learning task. Participants were instructed to learn which secondary patterns were associated with which primary patterns and prompts. The procedure for the test blocks was similar to that for the verbal learning task except that the test trials involved recognition rather than recall. Test trials began with the participant seeing a primary pattern and the first prompt, "A." Participants selected the correct pattern, using the computer mouse, from among four different patterns (three of which were distractors) displayed in a $2 \times 2$ 'pattern recognition' box in the center of the screen. Alternatively, the participant could select the letter "X" if the correct pattern was not recognized. Participants were given corrective feedback after each response. The participant then saw the same primary pattern with the second prompt and recognition box followed by the third prompt and recognition box. The patterns in the recognition box were different for each primary pattern and prompt, and changed randomly with each test trial.

In the Spatial Learning task, another nonverbal adaptation of the verbal learning task, the stimuli were arrays of dots,
and participants used a mouse click to continue rather than pressing “enter.” Participants were shown six primary locations, each of which was associated with three associated secondary locations.

On learning trials, participants first saw an array of dots on the screen with a primary location marked in green, followed by the prompt, “press A.” Once the participant pressed the cued letter, the prompt disappeared, and the cued letter appeared in the middle of the screen above the array of dots, and the marked location moved to a nearby, secondary location. The secondary location and letter remained on the screen until the participant clicked on the “continue” button on the computer screen with the mouse. Then, the primary location was shown again followed by the second prompt (i.e., “press B”), and after pressing the cued letter (“B”), the letter and the secondary location appeared and remained on the screen until the participant clicked to continue. The third prompt (i.e., “press C”) and the primary location then appeared. Again, the prompt disappeared once the participant pressed the cued letter, and the letter and the third secondary location appeared on the screen. This cycle was repeated until all six of the primary locations with their three associated secondary locations were presented; all three secondary locations were presented near the primary location. The array of dots used with each primary location was different in order to prevent participants from learning a particular pattern rather than a location in space. The order of presentation for the six primary locations and their associated memory items was different in each of the four learning blocks.

Test trials began with a primary location marked in the array of dots and the first prompt, “A,” the prompt letter appeared in the middle of the screen above the array of dots, participants were asked to select the correct secondary location that the primary location had moved to, using the computer mouse, from among the dots in the array. Alternatively, a participant could select the letter “X” if the secondary location could not be recalled. Participants were given corrective feedback after each response. The participant then saw the same primary location with a second prompt and secondary location followed by a third prompt and secondary location. Participants were tested for their memory of the three secondary locations associated with each primary location with the primary locations presented in the same order as the preceding learning block.

4.2.4. Fluid intelligence

Participants completed computerized adaptations of the Raven’s Advanced Progressive Matrices—Set II (RAPM) and the Woodcock Johnson Concept Formation (Concept) tests, as well as a pencil and paper version of the Shipley Institute of Living Scale Abstraction Subtest (Shipley). All tests were completed without a time limit.

In the RAPM, each problem contained a 3x3 matrix with one element missing and eight elements to choose from (Raven, Raven, & Court, 1998). Participants were asked to select the element that completed the matrix along both the rows and columns. Although the RAPM contains 36 problems, the task was automatically terminated if a participant failed to answer five out of six consecutive trials correctly. In the Concept test, each problem contained a colored shape (e.g., a yellow circle) or shapes within a box and a shape (e.g., a red circle) or shapes outside of the box (Woodcock, McGrew, & Mather, 2001). Participants were asked to give the rule that described why a shape is inside the box (e.g., shape must be yellow). Although the test contains 40 problems, administration followed the standard protocol by using the prescribed stopping rule as well as sample problems and feedback on incorrect responses. In the Shipley subtest, participants solved 20 series completion problems involving letters, digits, and words (Zachary, 2000).

5. Results

Table 2 presents descriptive statistics for each task and test, and Table 3 presents the correlations of each task and test with age, as well as their intercorrelations and their partial correlations with age controlled. Similar patterns were observed in the zero-order and first-order (partial) correlations. The two processing speed tasks were strongly correlated, as were the three learning tasks and the three fluid intelligence tests. The two spatial working memory tasks (parallel span and position span) were also strongly correlated, although both were only moderately correlated with the verbal working memory task (counting span). Notably, each of the three fluid intelligence tests was strongly correlated with each of the three-term learning tasks.

Next, a composite score was calculated for each participant on each construct (processing speed, working memory, associative learning, and gF) by taking the mean of the participant’s z-scores on the tasks or tests representing that construct. The reliability of the z-score composite for each construct was determined by entering the individual task z-scores into an alpha reliability analysis. Table 4 presents correlations among the constructs as well as measures of skew, kurtosis, and reliability for each of the four constructs just described as well as three other constructs to be described later. A repeated measures Analysis of Covariance with age as a covariate revealed a task x age interaction, \( F(3,76) = 10.08, p < .001 \), reflecting the fact that the rate of decrease in processing speed (−0.036 z-score units per year) was significantly greater than the rates of decrease in working memory, learning, and gF (−0.018, −0.019, and −0.019 z-score units per year, respectively): for all three comparisons, \( F(1,78) > 26.8, p < .01 \).

5.1. Cognitive cascade models

Path analyses were conducted using LISREL 8.80 (Jöreskog & Sörbom, 2007) in order to evaluate a series of cognitive cascade models describing possible relations among the constructs. Path analyses were conducted instead of using structural equation modeling (SEM) because of the number of constructs relative to the sample size. Despite this constraint, we wanted to take advantage of the fact that we had multiple measures of each construct, hence the use of z-score composites, and to be able to obtain parameter estimates free of the distorting effects of measurement error, as in SEM analyses. Therefore, the error for each construct was approximated using standardized alpha reliability for the construct and entered into the models as a fixed parameter (Jöreskog & Sörbom, 1993).
The fit of each model was evaluated using the following indices: chi square, which was not significant if the fit was good; the root mean square error of approximation (RMSEA), for which a value of less than .10 was considered to be "good" and values less than .05 to be "very good"; the comparative fit index (CFI), for which a value greater than .95 indicated a good fit; Akaike’s information criterion (AIC), for which smaller values indicate better fits; the standardized root mean residual (SRMR), for which smaller values indicated better fits. When possible, models were compared with chi-square difference tests in order to determine whether a model represented a significant improvement over a previously tested model.

Our fundamental concern in the present study was with the relations among age, processing speed, working memory, associative learning, and gF. Previous research involving these constructs has pointed to two possible cognitive cascades, one in which age-related slowing affects working memory, leading ultimately to declines in gF (Salthouse, 1991; Verhaeghen & Salthouse, 1997), and one in which slowing’s effect on working memory ultimately leads to decreases in learning ability (Kirasic et al., 1996).

To test the cognitive cascade hypothesis, we first specified a cognitive cascade model for complex associative learning. This model (Model 1A, depicted in Fig. 1) provided an excellent fit to the data (see Table 5). As suggested by the cognitive cascade, age-related slowing negatively impacted working memory, and the resultant decline in working memory then had a direct effect on associative learning. This model accounted for 49% variance in associative learning. When the model was modified by adding a direct path from age to learning in order to determine whether all of the age effects in associative learning were accounted for by processing speed and working memory, this additional path was not significant (t = −.84) and it did not improve the fit of the model, \( \chi^2_{\text{diff}} (1) = .75, p > .25 \) (Model 1B in Table 5).

Next, we specified a cognitive cascade in which age-related slowing negatively impacts working memory, and the resulting decline in working memory has direct effects on gF. This model (Model 2A, depicted in Fig. 1) provided a very good fit to the data (see Table 5). All of the paths hypothesized by the cognitive cascade model were significant, suggesting that age-related changes in gF are the result of a cognitive cascade. When the model was modified by adding a direct path from age to gF in order to determine whether all of the age effects in gF were accounted for by processing speed and working memory, the additional path was not significant (t = −.79) and the path did not significantly improve the model fit, \( \chi^2_{\text{diff}} (1) = .64, p > .25 \) (Model 2B in Table 5).

Although the good fits of Models 1A and 2A are consistent with the hypothesis that cognitive cascades underlie age and individual differences in both associative learning and gF, respectively, Model 2A only accounted for 49% of the variance in gF. Accordingly, we next sought to determine whether the extended cascade hypothesis, in which learning mediates the relation between working memory and gF, results in a model that increases the amount of variance accounted for. The extended cognitive cascade model (Model 3A, depicted in Fig. 1) provided an adequate fit to the data with a non-significant chi-square and high CFI (see Table 5) and accounted

**Table 2**
Descriptive statistics for all tasks.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Distance Judgment</th>
<th>Shape Judgment</th>
<th>Parallel Span</th>
<th>Position Span</th>
<th>Counting Span</th>
<th>Verbal Learning</th>
<th>Visual Learning</th>
<th>Spatial Learning</th>
<th>Concept Formation</th>
<th>Ravens Advanced</th>
<th>Shipley Abstraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>894</td>
<td>1067</td>
<td>46.53</td>
<td>36.49</td>
<td>27.00</td>
<td>144.53</td>
<td>224.40</td>
<td>217.90</td>
<td>27.40</td>
<td>14.60</td>
<td>15.49</td>
</tr>
<tr>
<td>SD</td>
<td>232</td>
<td>269</td>
<td>8.86</td>
<td>8.69</td>
<td>7.61</td>
<td>100.66</td>
<td>88.92</td>
<td>68.62</td>
<td>7.39</td>
<td>7.88</td>
<td>3.68</td>
</tr>
<tr>
<td>Skew</td>
<td>.82</td>
<td>.66</td>
<td>−0.14</td>
<td>0.23</td>
<td>0.66</td>
<td>0.58</td>
<td>−0.14</td>
<td>0.29</td>
<td>−0.61</td>
<td>0.09</td>
<td>−1.32</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>.84</td>
<td>.68</td>
<td>−0.02</td>
<td>−0.47</td>
<td>0.71</td>
<td>−0.69</td>
<td>−0.24</td>
<td>−1.07</td>
<td>0.24</td>
<td>−0.51</td>
<td>1.17</td>
</tr>
<tr>
<td>Reliability</td>
<td>.90</td>
<td>.96</td>
<td>.82</td>
<td>.83</td>
<td>.77</td>
<td>.93</td>
<td>.89</td>
<td>.91</td>
<td>.94</td>
<td>.88</td>
<td>.89</td>
</tr>
</tbody>
</table>

Note: RTs in milliseconds are reported for Distance Judgment and Shape Judgment; total items correctly recalled are reported for Parallel Span, Position Span, and Counting Span; learning tasks are reported as the sum of the percent correct on each of the four test blocks; raw scores are reported for Concept Formation, Ravens Advanced and Shipley Abstraction. Reliabilities for all measures except for the learning tasks were calculated using the Spearman-Brown split-half reliability formula; reliability for the learning tasks were calculated using the Cronbach’s Alpha reliability formula.

**Table 3**
Correlations and partial correlations (with age controlled).

<table>
<thead>
<tr>
<th>Task</th>
<th>Age</th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
<th>6.</th>
<th>7.</th>
<th>8.</th>
<th>9.</th>
<th>10.</th>
<th>11.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Distance Judgment</td>
<td>.41</td>
<td>.57</td>
<td>−.49</td>
<td>−.35</td>
<td>−.21</td>
<td>.05</td>
<td>−.19</td>
<td>−.25</td>
<td>−.29</td>
<td>−.31</td>
<td>−.27</td>
<td></td>
</tr>
<tr>
<td>2. Shape Judgment</td>
<td>.56</td>
<td>.66</td>
<td>−.29</td>
<td>−.21</td>
<td>−.10</td>
<td>−.03</td>
<td>−.13</td>
<td>−.09</td>
<td>−.28</td>
<td>−.23</td>
<td>−.20</td>
<td></td>
</tr>
<tr>
<td>3. Parallel Span</td>
<td>−.28</td>
<td>−.55</td>
<td>−.38</td>
<td>.72</td>
<td>.36</td>
<td>.29</td>
<td>.42</td>
<td>.56</td>
<td>.43</td>
<td>.49</td>
<td>.45</td>
<td></td>
</tr>
<tr>
<td>4. Position Span</td>
<td>−.29</td>
<td>−.42</td>
<td>−.33</td>
<td>.74</td>
<td>.36</td>
<td>.24</td>
<td>.27</td>
<td>.44</td>
<td>.31</td>
<td>.39</td>
<td>.32</td>
<td></td>
</tr>
<tr>
<td>5. Counting Span</td>
<td>−.19</td>
<td>−.27</td>
<td>−.19</td>
<td>.39</td>
<td>.40</td>
<td>.49</td>
<td>.40</td>
<td>.36</td>
<td>.21</td>
<td>.35</td>
<td>.31</td>
<td></td>
</tr>
<tr>
<td>6. Verbal Learning</td>
<td>−.25</td>
<td>−.06</td>
<td>−.11</td>
<td>.34</td>
<td>.30</td>
<td>.51</td>
<td>.25</td>
<td>.64</td>
<td>.65</td>
<td>.69</td>
<td>.57</td>
<td></td>
</tr>
<tr>
<td>7. Visual Learning</td>
<td>−.28</td>
<td>−.28</td>
<td>−.25</td>
<td>.59</td>
<td>.33</td>
<td>.43</td>
<td>.77</td>
<td>.64</td>
<td>.65</td>
<td>.69</td>
<td>.57</td>
<td></td>
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<tr>
<td>8. Spatial Learning</td>
<td>−.28</td>
<td>−.33</td>
<td>−.23</td>
<td>.46</td>
<td>.49</td>
<td>.40</td>
<td>.65</td>
<td>.67</td>
<td>.51</td>
<td>.60</td>
<td>.50</td>
<td></td>
</tr>
<tr>
<td>9. Concept Formation</td>
<td>−.34</td>
<td>−.39</td>
<td>−.41</td>
<td>.48</td>
<td>.38</td>
<td>.26</td>
<td>.54</td>
<td>.68</td>
<td>.56</td>
<td>.70</td>
<td>.62</td>
<td></td>
</tr>
<tr>
<td>10. Ravens Advanced</td>
<td>−.27</td>
<td>−.38</td>
<td>−.33</td>
<td>.53</td>
<td>.43</td>
<td>.38</td>
<td>.61</td>
<td>.71</td>
<td>.63</td>
<td>.73</td>
<td>.68</td>
<td></td>
</tr>
<tr>
<td>11. Shipley Abstraction</td>
<td>−.20</td>
<td>−.32</td>
<td>−.27</td>
<td>.48</td>
<td>.35</td>
<td>.34</td>
<td>.51</td>
<td>.59</td>
<td>.52</td>
<td>.64</td>
<td>.69</td>
<td></td>
</tr>
</tbody>
</table>

Note: Zero-order correlations are below the diagonal; First-order (age-partialled) correlations are above the diagonal. Correlations greater than .22 (shown in bold) are significant at the .05 level.
for 75% of the variance in \( g_F \). Importantly there was a strong path from learning to \( g_F \), indicating that more effective learners performed significantly better on fluid intelligence tests than poorer learners. However, the model RMSEA of .12 suggested that there might be an error in model specification. One potential error could be that learning does not fully mediate the relation between working memory and \( g_F \). Accordingly, the extended cognitive cascade was modified to include a direct path from working memory to fluid \( g_F \). However, this path was not significant, \( t = 1.43 \), and failed to improve the model fit, \( \chi^2_{\text{diff}}(1) = 2.78, p > .05 \) (see Model 3B, Table 5), consistent with the hypothesis that associative learning mediates the relation between working memory and \( g_F \).

An alternative potential error in the model specification could be that working memory and associative learning do not completely mediate the effect of processing speed on \( g_F \). Accordingly, the extended cognitive cascade model was modified to include a direct path from speed to \( g_F \) (see Fig. 1, Model 3C). This modification improved the model fit significantly, \( \chi^2_{\text{diff}}(1) = 7.80, p < .01 \) (see Model 3C, Table 5), resulting in an excellent fit to the data, as indicated by an RMSEA less than .0005, and a CFA greater than .995, as well as improvements in the other fit indices over those for the extended cascade without this additional path (Model 3A). In contrast, adding a path from speed to learning instead of from speed to \( g_F \) did not improve the fit of the extended cascade model, \( \chi^2_{\text{diff}}(1) = 0.52, p > .05 \), and the path itself was not significant (\( t = 0.50 \)), indicating that the speed path in Model 3C captures variance in \( g_F \) that is not associated with learning ability. Notably, Model 3C accounted for 79% of the variance in \( g_F \).

### 5.2. Decomposing learning performance

The models tested thus far support the hypothesis of an extended cognitive cascade in which age-related slowing

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**Table 4**

Correlations and descriptive statistics for all construct composites.

<table>
<thead>
<tr>
<th>Measure</th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
<th>6.</th>
<th>7.</th>
<th>8.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>2. WM</td>
<td>-.48</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Learn</td>
<td>-.26</td>
<td>.59</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. (g_F)</td>
<td>-.43</td>
<td>.55</td>
<td>.75</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>5. SM</td>
<td>-.33</td>
<td>.59</td>
<td>.85</td>
<td>.63</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Learn 4</td>
<td>-.21</td>
<td>.55</td>
<td>.97</td>
<td>.76</td>
<td>.75</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>7. Learn R</td>
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<td>.31</td>
<td>.71</td>
<td>.59</td>
<td>.31</td>
<td>.85</td>
<td></td>
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<tr>
<td>8. Age</td>
<td>.53</td>
<td>-.31</td>
<td>-.30</td>
<td>-.30</td>
<td>-.30</td>
<td>-.27</td>
<td>-.18</td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>1.82</td>
<td>2.46</td>
<td>2.68</td>
<td>2.67</td>
<td>2.37</td>
<td>2.62</td>
<td>2.27</td>
<td>13.99</td>
</tr>
<tr>
<td>Skewness</td>
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<td>0.40</td>
<td>0.21</td>
<td>-.62</td>
<td>.39</td>
<td>-.10</td>
<td>-.03</td>
<td>0.05</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.31</td>
<td>0.23</td>
<td>-.65</td>
<td>0.02</td>
<td>.39</td>
<td>-1.14</td>
<td>-.86</td>
<td>-1.09</td>
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<tr>
<td>Reliability</td>
<td>0.30</td>
<td>0.76</td>
<td>0.87</td>
<td>0.87</td>
<td>0.70</td>
<td>0.83</td>
<td>0.61</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: PS = Processing Speed; WM = Working Memory; Learn = Learning (Total); \( g_F \) = Fluid Intelligence; SM = Secondary Memory—Block 1; Learn 4 = Block 4; Learn R = Learning Residuals. Correlations greater than .26 (shown in bold) are significant at the .05 level.
affects working memory which then affects associative learning, which in turn affects gF, although there is also some evidence of a direct effect of slowing on gF. These results are consistent with the idea that learning mediates the relation between working memory and gF. It is obvious, however, that the complex associative learning tasks measure secondary memory as well as learning, and it is possible that the secondary memory component of our learning tasks is the reason that learning appears to mediate the effect of working memory on gF.

In order to address this possibility, we partitioned performance on the learning tasks into two constructs: secondary memory and learning. For the secondary memory construct, we examined performance on the first block of each associative learning task (i.e., verbal learning, visual learning, and spatial learning), and for the learning construct, we examined performance on the fourth block (i.e., after extensive practice). Because performance on the first block of the verbal learning task was quite positively skewed (skew = 2.34), we transformed first and fourth block scores on all three learning tasks by taking their square roots. We then created z-score composites for these secondary memory and learning measures (see Table 4 for the distributional characteristics of these composite scores).

We tested an extended cognitive cascade model that was similar to Model 3C, the previously best-fitting model, except that the unitary learning construct was replaced by two constructs, one representing secondary memory (as assessed on the first test block of each learning task) and another representing learning (as assessed on the fourth and final test block of each learning task). According to this new model (Model 4, see the upper panel of Fig. 2), working memory affects secondary memory, which affects learning, which in turn affects gF. This extended cascade model provided an excellent fit to the data, as indicated by a nonsignificant chi square, and an RMSEA less than .05, as well as other very good fit statistics (see Table 5).

Performance on the final block of the learning tasks undoubtedly still contains variance attributable to performance on the first block, and hence to secondary memory, on all three learning tasks. We then created z-score composites for these secondary memory and learning measures (see Table 4 for the distributional characteristics of these composite scores).

![Fig. 2](image_url) Extended cognitive cascade models with separate secondary memory and associative learning constructs. In both Models 4 and 5, secondary memory (SM) is indexed by performance on Block 1 of the learning tasks; in Model 4, Learning is indexed by performance on Block 4 of the learning task, and in Model 5, Learning is indexed by the residuals of the regression of Block 4 on Block 1.
and this may explain the high correlation between these two constructs in Model 4. Therefore, we next attempted to remove this variance by regressing fourth block performance for each task on the corresponding first block measure, in order to obtain the standardized residuals for each learning task. These standardized residuals were then combined to form a z-score composite measure of learning ability from which secondary memory had been partialled out.

We then tested an extended cascade model (Model 5, see the lower panel of Fig. 2) in which working memory had direct effects on both the secondary memory and learning (residual) constructs, each of which then had a direct effect on \( g_F \), in order to assess the relative contributions of secondary memory and associative learning to \( g_F \). The fit of this model was also excellent with a nonsignificant chi square and a low RMSEA as well as other good fit statistics (see Model 5, Table 5). Examination of the path coefficients for Model 5 (see Fig. 2) reveals that working memory is related to the ability to retrieve information from secondary memory and also to learning ability, each of which has a significant direct effect on \( g_F \).

Finally, Unsworth and Engle (2007) have suggested that individual differences in working memory are to a large extent driven by individual differences in secondary memory. Accordingly, we tested an alternative cascade model in which age-related declines in processing speed negatively impact secondary memory, which in turn affects working memory, and the resulting changes in working memory directly affect \( g_F \) (see Model 6, Table 5). Consistent with Unsworth and Engle’s suggestion, individual differences in secondary memory predicted individual differences in working memory and working memory predicted \( g_F \). However, this model only accounted for 59% of the variance in \( g_F \), compared to the 75% accounted for by a comparable extended cognitive cascade (Model 3A). Taken together, the present results suggest that secondary memory and associative learning are both important for understanding the relation between working memory and \( g_F \), and that the sequencing of the constructs being modeled is critical.

5.3. Multiple regression analyses

Finally, multiple linear regression was used to assess the contributions of the various constructs to predicting \( g_F \) outside the context of the extended cascade model. Analysis of a regression model in which age, processing speed, working memory, and learning were independent variables and \( g_F \) was the dependent variable revealed that although the model accounted for 62.1% of the variance in \( g_F \), only processing speed and learning contributed significantly to the prediction. Indeed, a regression model in which processing speed, secondary memory, and learning were the only independent variables accounted for 64.1% of the variance in \( g_F \), only 0.6% less than when age and working memory were also included. Processing speed uniquely accounted for 7.0% of the variance in \( g_F \), secondary memory for 12.7%, and learning 19.7%, with 24.7% of the variance shared between two or more constructs. These findings are consistent with the extended cascade model (Model 5) in that neither age nor working memory explained variance in \( g_F \) that could not be explained by the other three constructs, and more than half of the 18.8% of the variance in \( g_F \) attributable to speed was shared with secondary memory and learning.

6. Discussion

The present study tested cognitive cascade models of the relations among age, processing speed, working memory, associative learning, and \( g_F \) across the adult lifespan. According to the cognitive cascade hypothesis, age-related slowing affects working memory, which in turn affects higher-order cognitive functions, and this hypothesis was confirmed for both associative learning and \( g_F \) separately. Further path analyses revealed that associative learning mediated the relation between working memory and \( g_F \), consistent with an extended cascade model. Moreover, adding a direct path from speed to \( g_F \) to the extended cascade model resulted in an excellent fit. When performance on the associative learning tasks was decomposed into two separate components, secondary memory plus learning itself, analyses revealed that learning and secondary memory were both related to \( g_F \). Taken together, these results highlight the importance of associative learning in the cognitive cascade and suggest a possible explanation for the relation between working memory and \( g_F \).

The results of multiple regression analyses provided converging evidence for some of the findings from the path analyses. Like path analysis, multiple regression revealed that when the relations of age, processing speed, working memory, and learning to \( g_F \) were examined simultaneously, only the contributions of processing speed and learning were significant. This is not to say that age and working memory were unrelated to \( g_F \), of course, as all three of these variables were significantly correlated. Nevertheless, the variance in \( g_F \) explained by age and working memory in the current study could also be explained by other constructs which accounted for significant additional variance, over and above that which they shared with age and working memory.

In cognitive aging research, it is generally accepted that age is not a cause of age differences in cognition. Rather, age serves as a proxy for the age-related changes in fundamental mechanisms that do affect cognitive abilities, and the goal of cognitive aging research is to discover what these mechanisms are. One common approach to achieving this goal is to try and discover what potentially causal variables can account for the variance otherwise accounted for by the proxy variable, age. Path analysis refines this approach by testing specific hypotheses regarding the relations, or lack
thereof, among potentially causal and caused variables. Although it cannot establish causality, it can assess whether data are consistent with hypotheses regarding causal relations, and the present data are clearly consistent with the hypothesis of an extended cognitive cascade.

6.1. Processing speed and the cognitive cascade

In the current study, and consistent with previous reports, age-related differences in processing speed affected $g_F$ both directly (Gregory et al., 2009; Verhaeghen & Salthouse, 1997) and indirectly through their effect on working memory (Fry & Hale, 1996; Kail & Salthouse, 1994; Salthouse, 1991). Salthouse (1996) has hypothesized that age-related slowing impacts other aspects of cognitive function via both a limited time mechanism and a simultaneity mechanism. According to the limited time mechanism, when older adults perform a task the fact that they are slower either leaves them with insufficient time to perform at least some task components or causes them to perform the components less accurately. This mechanism, which involves external time constraints, would appear to play a minimal role in the current study because the fluid intelligence tests were self-paced.

According to the simultaneity mechanism, which involves internal constraints, the availability of information (both that which was originally provided as well as the information that was internally generated) may decrease with time. That is, as individuals switch back and forth between two or more different mental operations on complicated tasks, those who take longer to perform one operation may have less information available to them for the next operation. The direct path from speed to $g_F$ may be due to the simultaneity mechanism. For example, the longer an older adult participant took to discern the rule across a row in a particular problem, the more time would have passed since the evaluation of rules across the other rows and across columns, and the greater the likelihood the problem would not be solved correctly. The direct path from speed to $g_F$, although consistent with previous reports (Gregory et al., 2009; Verhaeghen & Salthouse, 1997), was relatively weak compared to the path from speed to working memory or the path from associative learning to $g_F$. Further, the path from speed to $g_F$ was not a hypothesized path in the extended cascade model, and thus an extended cognitive cascade model with this path should be replicated in an independent sample.

6.2. Working memory and learning

Working memory has been described as a multi-faceted construct that has been hypothesized to tap a wide variety of processes, including not only temporary storage, but also controlled attention, relational integration, interference control, and retrieval from secondary memory (Kane, Conway, Hambrick, & Engle, 2007; Oberauer, Süß, Wilhelm, & Wittman, 2008; Unsworth, 2010). Although some researchers have suggested that retrieval from secondary memory is the major reason for the relation between working memory and $g_F$ (Mogle et al., 2008), others have argued that this relation depends on much more than the ability to retrieve information from secondary memory (Shelton et al., 2010; Unsworth et al., 2009).

For example, Unsworth and Spillers (2010) reported that working memory capacity is driven by individual differences in attentional control as well as secondary memory. In addition, the role of memory control processes in working memory was highlighted in a study by Unsworth (2010) in which a general memory construct composed of measures of both working memory and memory control processes was predictive of $g_F$. Unsworth suggested that these memory control processes include elaboration at encoding, generating internal cues at retrieval, and monitoring the products of retrieval. These processes should also be important in learning tasks like those studied here, and temporary storage is undoubtedly important for learning as well. Consistent with this view, the results of the current study indicate that the participants with greater working memory capacity were better learners, which may explain why the variance in $g_F$ accounted for by working memory was shared with learning.

6.3. Decomposing associative learning

The associative learning tasks used in the present study involved both learning and memory, raising the question of which component, learning or memory, is responsible for mediating the effect of working memory on $g_F$. To address this issue, we first examined the performance on the learning tasks after participants’ initial exposure to the to-be-remembered material as a measure of secondary memory and performance after repeated exposure as a measure of learning plus memory. The fit of an extended cognitive cascade model in which working memory affects secondary memory, which in turn affects learning, and learning ultimately predicts $g_F$ (Model 4), is consistent with the hypothesis that the learning component, as assessed after repeated exposure, plays a mediating role in the relation between working memory and $g_F$. The strength of this evidence is limited, however, by the fact that performance after repeated exposure, although it does measure learning ability, still depends on secondary memory.

To tease apart the contributions of the secondary memory and learning components of the associative learning tasks, learning was operationally redefined as the residual variance in performance following repeated exposure after statistically controlling for secondary memory (i.e., initial performance on the learning tasks). Using this definition, we examined an extended cognitive cascade model (Model 5) in which there were separate paths from working memory to both secondary memory and learning as well as paths from both secondary memory and learning to $g_F$. Individual differences in both the ability to learn and the ability to retrieve information from secondary memory were found to mediate the relation between working memory and $g_F$.

These results indicate that individuals with greater working memory capacity tend to have better delayed recall and are more effective learners, and that these latter two abilities, although related, are at least somewhat independent. Moreover, both of these abilities are important for $g_F$. This is not to say that other cognitive abilities tapped by working memory tasks (e.g., attentional control; Unsworth & Spillers, 2010) do not also play a role. However, assessing their contributions and exactly how they relate to secondary memory and learning will require future studies that explicitly measure all of these constructs in order to directly
address this issue. Further, given the relatively small sample size in the present study, a replication using a larger sample is needed to verify the relations among the constructs modeled here. Nevertheless, the present findings suggest that across the adult portion of the life span, complex associative learning may play an important role in the extended cognitive cascade underlying age and individual differences in \( g_F \).

6.4. Learning and fluid intelligence

The finding that working memory does not appear to directly affect \( g_F \), but rather does so only indirectly, is consistent with a growing consensus that the concurrent processing requirement, which distinguishes working memory tasks like those in the present study from other short-term storage measures, is not responsible for the relation between working memory and fluid intelligence (Colom et al., 2006; Colom et al., 2008; Oberauer, Lange, & Engle, 2004). Further, the concurrent processing requirement of working memory tasks does not make them more age-sensitive than simple span (short-term memory) tasks. Indeed, performance on both types of tasks declines at the same rate across the adult portion of the life span when they both involve the same kind of memory items (Hale et al., 2011).

As theorists have moved away from the idea that individual differences in executive function, controlled attention, inhibitory ability or resistance to interference drive the relation between working memory and fluid intelligence, they have increasingly emphasized instead the importance of the storage and retrieval functions tapped by working memory tasks (e.g., Colom et al., 2008; Unsworth & Engle, 2007). The present findings are consistent with this view, and in addition, suggest that the storage and retrieval functions tapped by other types of memory tasks, particularly learning tasks that involve repeated exposure and accumulation of information in memory, may also play a fundamental role in predicting fluid intelligence in adults of all ages.

What remains to be determined is the exact mechanism(s) by which learning affects \( g_F \). Associative learning appears to involve two processes that have been hypothesized to underlie \( g_F \): relational integration (Oberauer et al., 2008) and contextual retrieval (Unsworth & Engle, 2007). For example, the complex associative learning tasks used in the present study require binding together three stimulus elements (a cue, a prompt, and a memory item) into a structural representation (relational integration) on learning trials and then retrieving the missing third element (the memory item) on test trials whenever the first two elements (the cue and prompt) are presented (contextual retrieval).

The processes of relational integration and contextual retrieval are also involved in performing working memory tasks. However, unlike some working memory tasks (e.g., Counting Span and Parallel Span in the present study), which require binding elements together temporarily on one trial and then unbinding them and rebinding some of the same elements in a different order or configuration on the next trial, associative learning tasks require sustained retention of associated elements. Thus, associative learning tasks may be tapping the ability to bind together multiple elements and then keep them bound while going on to bind new sets of elements, which is an important part of solving successive problems on fluid intelligence tests. That is, these tests frequently are constructed in such a way that the ordering of the problems, from easier to increasingly more difficult, allows or may even facilitate learning rules on early problems that will prove useful in solving later problems (Carlstedt, Gustafsson, & Ullstadius, 2000; Verguts & De Boeck, 2002b). Thus, learning may predict \( g_F \) because fluid intelligence tests implicitly measure learning.

It appears that certain types of learning are not related to intelligence. For example, Estes (1982) concluded that habitual learning and conditioning, both classical and operant, are not related to intelligence. Paired associate learning and serial learning are also thought to have little relation to intelligence when these tasks can be accomplished using rehearsal rather than elaboration and manipulation of information (Jensen, 1969; Mackintosh, 1998). Consistent with these distinctions between types of learning, Williams and Pearlberg (2006) reported that paired associative learning and free recall learning were not correlated with \( g_F \), whereas complex associative learning was strongly correlated with \( g_F \). In contrast, Kaufman et al. (2009) reported that both paired associative learning and complex associative learning correlate and predict \( g_F \). These two studies point to different conclusions. Kaufman et al. (2009) concluded that associative learning in general can predict \( g_F \), whereas Williams and Pearlberg concluded that complex associative learning is special in its ability to predict individual differences in \( g_F \). Given the inconsistency in the literature, further research will be needed to determine whether paired associate learning and complex associative learning really do differ in their relations with \( g_F \).

7. Conclusion

The current findings suggest that at least part of the reason why working memory predicts \( g_F \) is because individuals who have greater working memory are the same individuals who have greater secondary memory and learning ability. These findings not only have theoretical implications, they may have real world implications as well. For example, Schmidt and Hunter (2004) noted that intelligence is predictive of performance on jobs of all kinds and at all levels. They argued that the reason for this is twofold. First, the amount of job-related knowledge required to perform even apparently simple jobs is much greater than might have been expected. Second, people who are higher in general mental ability acquire more job-related knowledge and they acquire it faster than those of lower ability. Thus, the major effect of general mental ability is on job-related knowledge acquisition, which turns out to be the major determinant of job performance. Those who can learn more, faster, will do their jobs better. It is possible that associative learning tasks may prove to be even better predictors of job performance than general ability tests because the learning tasks measure learning directly and are highly predictive of \( g_F \). Independent of whether these tasks prove useful in such applications, however, the present findings clearly establish a role for complex associative learning in the cognitive cascade underlying age and individual differences in \( g_F \).