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Self-Regulation and Recall: Growth Curve Modeling of Intervention Outcomes for Older Adults

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Abstract

Memory training has often been supported as a potential means to improve performance for older adults. Less often studied are the characteristics of trainees that benefit most from training. Using a self-regulatory perspective, the current project examined a latent growth curve model to predict training-related gains for middle-aged and older adult trainees from individual differences (e.g., education), information processing skills (strategy use) and self-regulatory factors such as self-efficacy, control, and active engagement in training. For name recall, a model including strategy usage and strategy change as predictors of memory gain, along with self-efficacy and self-efficacy change, showed comparable fit to a more parsimonious model including only self-efficacy variables as predictors. The best fit to the text recall data was a model focusing on self-efficacy change as the main predictor of memory change, and that model showed significantly better fit than a model also including strategy usage variables as predictors. In these models, overall performance was significantly predicted by age and memory self-efficacy, and subsequent training-related gains in performance were best predicted directly by change in self-efficacy (text recall), or indirectly through the impact of active engagement and self-efficacy on gains (name recall). These results underscore the benefits of targeting self-regulatory factors in intervention programs designed to improve memory skills.

Keywords

self-regulation; memory training; older adults

Training has been widely studied as a potential means to improve memory for older adults and most research has supported the effectiveness of such programs (Floyd & Scogin, 1997; Rebok, Carlson, & Langbaum, 2007; Verhaeghen, Marcoen, & Goossens, 1992). One issue that has received scant attention, however, is the prediction of training outcomes. Knowing who benefits most from training would permit us to focus training programs on those individuals, and encourage development of alternative intervention approaches for individuals who benefit less from traditional training (e.g., Baldi, Plude, & Schwartz, 1996;

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[1]This training program was conducted in two waves (basic results for first wave were reported in West et al., 2008; second wave results and self-help data were reported in Hastings & West, 2009). Both waves of data are included here, with group training participants only, because ratings for level of engagement were made during group sessions which the self-help and control participants did not attend.

[2]Some might argue that two data points cannot effectively estimate change, thus we reran our Figure 3 model replacing self-efficacy intercept and slope with self-efficacy (*SE*) week 1 and *SE* week 9 as separate variables predicting memory slope and intercept (and week 1 *SE* predicting week 9 *SE*). These models showed equivalent fit to the ones reported here, but for conceptual reasons we preferred to represent self-efficacy intercept and slope using a growth curve approach.

Hastings & West, 2009; Rebok et al., 2007). Similarly, knowing what mechanisms drive training effects would contribute to designing more effective future training programs. This study used latent growth curve modeling to examine multiple factors that might predict memory training outcomes for middle-aged and older adult trainees.

Successful training outcomes depend on the investment of time and effort by trainees to learn and apply the knowledge gained in the intervention, that is, they require self-regulatory control. Self-regulation is the process by which individuals monitor and take charge of their own cognitive outcomes (Miller & West, 2010; Stine-Morrow, Shake, Miles, & Noh, 2006b). Based on their information-processing skills and self-perceptions of their ability to successfully activate these skills when needed, individuals can increase task engagement to meet cognitive goals (Stine-Morrow, Miller, & Hertzog, 2006a) or withdraw from task effort, resulting in a negative outcome (West, Welch, & Thorn, 2001). From this perspective, cognitive success is driven by information processing skills (strategy use, attentional allocation, perceptual speed, working memory) and self-regulatory factors (metamemory, self-monitoring, motivation, self-efficacy, performance anxiety), as well as individual difference factors that might covary with these, such as age and education (see Figure 1). The potential influence of many of these variables has been discussed for decades (e.g., Dunlosky & Hertzog, 1998a; West & Tomer, 1989), yet research predicting training outcomes is sparse. Furthermore, most studies have focused on one or two predictors of training effects rather than using a multivariate approach to examine their relative influence.

With respect to individual differences, it is clear that general health or mental status could be a factor in training benefit (Hill & Bäckman, 2000; Rasmussen, Rebok, Bylsma, & Brandt, 1999), and that education may affect the gains resulting from supportive learning conditions (Bagwell & West, 2008; Hill, Wahlin, Win-blad, & Bäckman, 1995). Metaanalysis has also shown that older trainees gain less than younger trainees (Verhaeghen et al., 1992). However, age differences may be acting as a proxy for other variables in some previous studies—such as education, self-efficacy, or health status, all of which tend to decline with age. Assessment of multivariate models is useful to tease out the relative influence of these factors.

Training studies looking at information processing skills have focused on strategies, cognitive test batteries, and mental speed as potential predictors of training outcomes. Kliegl, Smith, and Baltes (1990) tested whether training gains on a word list could be predicted by pretests on cognitive ability. Mental speed emerged as the significant predictor of training-related improvement. Similarly, Verhaeghen and Marcoen (1996) found that mental speed affected list recall at posttest, through its influence on associative memory and strategic use of rehearsal. There is evidence that strategy use affects working memory span (McNamara & Scott, 2001; Turley-Ames & Whit-field, 2003), paired associate memory, and free recall (Bailey, Dunlosky, & Hertzog, 2009; Dunlosky & Hertzog, 1998b; Saczynski, Rebok, Whitfield, & Plude, 2007). In addition, interventions that target strategies yield improvements in memory performance, suggesting that strategy use may be a key mechanism for improving memory (e.g., Lachman & Andreoletti, 2006; West, Bagwell, & Dark-Freudeman, 2008). However, research that focuses directly on the impact of strategy use or speed on training-related *improvement* on memory tasks is lacking. Thus, we have included mental speed and strategy use in our research.

Key self-regulatory beliefs such as anxiety about memory performance, control, and memory self-efficacy have been considered in previous intervention research. In several studies, pretraining programs aimed at relaxation and relieving anxiety yielded more pronounced training gains than strategy training alone (Stigsdotter & Bäckman, 1989; Yesavage, Lapp, & Sheikh, 1989). The influence of other self-regulatory factors is less clear, although there are theoretical reasons to expect motivation (Stine-Morrow et al., 2006a), self-efficacy (Valentijn et al., 2006; West, Dark-Freudeman, & Bagwell, 2009) and locus of control beliefs (Miller & Lachman, 1999) to be important, as these should all influence willingness to invest effort during training. For instance, Verhaeghen and Marcoen (1996) found noncompliance with training recommendations to be important. Also related to motivation to invest effort, Bissig and Lustig (2007) reported that self-initiation of cognitive control predicted training-related improvement, and Bagwell and West (2008) showed that gains were higher for those most actively engaged in training. Similarly, memory self-efficacy is often related to memory performance change over time, both in longitudinal studies (Valentijn et al., 2006) and in single session studies of goal-related gains (West et al., 2009), so one would expect self-efficacy levels to change along with memory gains in an intervention. However, to our knowledge, memory self-efficacy has not been examined as a time-varying covariate of performance change, such that *change* in memory self-efficacy predicts *change* in memory performance. In this research, self-efficacy, locus of control for memory, and active engagement in training were all considered as possible self-regulatory predictors of training-related memory gain.

Thus, previous literature on training indicated that a range of individual differences (age, education, health), information processing skills (mental speed, strategy use), and self-regulatory factors (self-efficacy, anxiety, control beliefs, engagement) could have an impact on training outcomes, although many of these factors have been investigated in only a few studies. The current project extends past work by using a growth curve model to predict recall gains across training. Examining a broad range of factors in one multivariate model affords a more comprehensive view of mechanisms for training-related gains, allowing for examination of both direct and indirect effects. Given a dearth of studies using multivariate growth models, this research should be seen as more exploratory than confirmatory, because we were testing multiple potential predictors of memory gain: individual difference factors, information processing skills, and self-regulatory variables. Nevertheless, based on theory and past research, we had specific expectations about the particular relationships that would be most likely to be significant.

Individual differences: This sample represented a large age range across middle-age and older adulthood (age 54 and up), but not as large as the age range employed in most training studies showing that younger adults in their 20s advanced more in training than older adults. We expected that age might predict baseline scores but age was not expected to predict training-related *gains* with other correlated factors in the model. Second, this sample represented a wider variation in education (8 to 24 years) than past studies whose participants typically were high school or college educated, leading to a prediction that individuals with more education would have higher baseline skills, and learn more from training.

Information processing skills: In both recall tasks, participants were given a relatively difficult memory task (24 sentences or 24 names to recall) with five minutes for encoding. Under these study conditions, we did not expect mental speed to be a key predictor, but thought that strategy usage might predict performance and memory gains.

Self-regulatory factors: Given that this training program strongly encouraged positive beliefs about one’s potential to improve memory, and encouraged individuals to work on their memory regularly at home and in the course, we expected beliefs and effort to be influential predictors. Thus, we included selfregulatory factors such as self-efficacy, locus of control, and active engagement in training to predict gains.

Method

Participants

Participants were recruited from congregate living facilities, lifelong learning programs, newspaper ads, and a participant registry. Participants ($N = 7$) were eliminated for potential cognitive problems (e.g., stroke, anticholinergic medications, or difficulty following instructions). Trainees included 136 adults, aged 54–92 ($M = 70.5$, $SD = 7.7$). The sample consisted mostly of women (102 female, 34 male) who were well-educated (range = 8 to 25 years, $M = 15.4$ years of education, $SD = 3.0$), and healthy ($M = 3.0$, $SD = 1.6$ on a self-rated health scale of 1–10, with 1 as *excellent health*). Based on Bentler (1985), this sample size was appropriate for a model estimating 27 parameters.

Training Procedures

Each of six weekly lessons taken from a training manual included written strategy instruction, practice activities, and readings. Lesson 1 introduced basic memory processes (completed as homework after the week 1 pretest). Lessons 2, 3, and 4 (two hours each) provided training on five strategies—organization, association, the image-name-match method (West, 1995), PQRST (West, 1985), active observation (careful focusing of attention)—and readings about aging and memory. These sessions began by reviewing homework in small group discussions; then the instructor taught a new strategy following the manual, led practice exercises, and assigned readings and more practice for homework. Tasks for the practice exercises in some cases were similar to the ones used in the assessment (e.g., text and list recall) and in some cases were quite different (e.g., object location recall, learning names of fellow trainees) from the assessment activities. Week 5 was an evaluation session, so Lesson 5 involved homework that summarized past sessions and emphasized control over memory in one's daily life. Lesson 6, presented in a 2-hr group session, explained methods for continued use of effective strategies at home. Participants had the opportunity to ask questions and participate in discussion at all four sessions (total training = eight hours). Homework completion (readings, with questions to answer, and practice exercises) was evaluated by the instructor every week (for additional detail, see West et al., 2008).

Participants were randomly assigned to serve as wait-list controls, or to receive group training or self-help training (working through the manual on their own). This report focuses on the group trainees.[1] The training program was designed to teach memory strategies and to increase memory self-efficacy: (a) practice exercises were organized from easy to difficult, to provide early mastery experience before individuals tackled challenging tasks; (b) participants received regular positive feedback and encouragement (i.e., verbal persuasion) to adopt positive memory beliefs (e.g., readings emphasized that memory is controllable and that extensive practice could lead to success); (c) trainees observed instructors and other participants modeling strategies; and (d) training was slowly paced to minimize stress about performance.

Assessment

Performance was assessed at a week-1 pretest, week-5 posttest and week-9 follow-up. Years of education, age, and self-rated health (scale from 1 to 10) were reported at week 1. Due to the length of the two beliefs questionnaires, they were administered only at week 1 and week 9 to allow time for training-related questions and answers after the evaluation was completed on week 5. Recall and information processing measures were assessed at all three occasions.

Beliefs

Participants completed the Memory Self-Efficacy Questionnaire (MSEQ-4; West, Bagwell, & Dark-Freudeman, 2005) to rate their perceived efficacy for object location, story, name, and grocery list recall, with five items for each scale. Each item was rated from 0–100% (0 = *I cannot do it*; 100 = *100% sure I could do it*) The 20 responses were averaged to obtain an overall score for memory self-efficacy strength (α= .94). Three Metamemory in Adulthood (MIA) subscales consisted of 39 items (Dixon, Hultsch, & Hertzog, 1988). Each was rated on a 1 to 5 scale and scores were averaged across each subscale; high scores represented high control beliefs for memory, high importance for memory achievement, and high anxiety about memory. Other MIA subscales (e.g., capacity, change) were not administered, due to their conceptual overlap with the MSEQ-4.

Active Engagement

A rating scale assessed the degree to which individuals were actively engaged in training, with 5 as *very actively engaged* and 1 as *unengaged*. These ratings were made without reference to any performance data, which were not available at the time the ratings were made. Ratings were based on attendance, homework completion, the quality of questions asked in class, involvement in small-group discussions in class, ability to answer questions when called upon, and general class attentiveness. Two trainers assigned ratings to the first 40 participants, with no differences between raters of more than one point on the scale, and strong interrater agreement (r = .90, p < .001); subsequently, disagreements were settled in discussion, and one trainer completed the remainder of the ratings.

Text Recall and Information Processing Measures

At pretest, vocabulary was assessed (Shipley, 1940) and the WAIS–R Digit Symbol (Wechsler, 1981) was used as an assessment of perceptual speed; it is known to influence both strategy usage and memory performance (Verhaeghen & Marcoen, 1996).

To assess memory over time, participants completed name, list, and text recall measures, at two levels of difficulty at all test sessions. Four matched stories, roughly equivalent in number of sentences, number of details, and reading level (Dixon, Hultsch, & Hertzog, 1989) were randomly assigned across the three assessment sessions. Participants completed a Level 1 (eight sentences) and a Level 2 (24 sentence) text recall task, using the same narrative, in each session. For the Level 2 test used in these analyses, due to larger training effects, participants studied the text for five minutes and then wrote down all the details they could remember. Protocols were scored with one point for each idea unit recalled, then transformed into a percentage score (range = 0–100), indicating how many ideas were recalled from the total possible to-be-remembered ideas in the text.

After Level 2 text recall, participants completed a self-report strategy checklist including items like I concentrated and paid attention, I noted the main idea, or *I covered the story and tested myself*. Each step in the PQRST was represented in the checklist (e.g., noting the main idea represented the Preview step and testing oneself represented the Test step), such that participants who used more steps in the trained strategy received higher strategy usage scores. Participants selected all strategies they had utilized (possible range = 0 to 15) and had an opportunity to list any other strategies that were not provided on the checklist. Several researchers have supported the validity of using self-report strategy questionnaires (Dunlosky & Hertzog, 1998a; West et al., 2008).

Participants completed a Level 1 (12 names and faces) and a Level 2 (24 names and faces) name recall task in each session. For the Level 2 test used in these analyses, participants studied the names and faces in color for five minutes, then saw the faces only and wrote down the name that went with each face. The dependent measure was the correct number of names recalled (range = 0–24). After Level 2 name recall, participants completed a selfreport strategy checklist including items like *I made a mental image* or *I tested myself.* Each step in the image-name-match method was represented in the checklist (e.g., *I tried to pick out prominent features*), such that participants who used more steps in the trained strategy received higher strategy usage scores. Participants selected all strategies they had utilized (possible range = 0 to 16) and had an opportunity to list any other strategies that were not provided on the checklist.

Results

Preliminary Analyses

Initial analyses examined degree of change over time for measures that had shown significant training effects (West et al., 2008): MIA locus of control for memory, memory self-efficacy, strategy usage for stories and names, name recall, and text recall. There were no significant training-related changes in other MIA measures or list recall performance. Those measures that had shown training-related gain were evaluated in repeated measures analyses. Text recall performance significantly increased from week 1 to week 9, $F(2, 270) = 62.9$, $p < .001$, $\eta_p^2 = .32$ = .32. There were both significant linear, $F(1, 135) = 82.6$, $p < .001$, $\eta_p^2 = .32$ = .38, and quadratic, $F(1, 135) = 35.3$, $p < .001$, $\eta_p^2 = .32$ = .21, components in this change. For name recall, performance significantly increased from week 1 to week 9, $F(2, 270) = 45.6$, $p < .001$, $\eta_p^2 = .32$ = .25. There were both significant linear, $F(1, 135) = 75.4$, $p < .001$, $\eta_p^2 = .32$ = .36, and quadratic, $F(1, 135) = 15.1$, $p < .001$, $\eta_p^2 = .32$ = .10, components for this change. For both recall measures, performance significantly improved from week 1 to week 5, and from week 1 to week 9, with maintenance and no significant change from week 5 to week 9. Strategy usage for stories showed linear increases over time $F(1, 135) = 15.7$, $p < .001$, $\eta_p^2 = .32$ = .10, and name strategies showed significant linear, $F(1, 135) = 37.4$, $p < .001$, $\eta_p^2 = .32$ = .33, and quadratic change, $F(1, 135) = 8.6$, $p < .005$, $\eta_p^2 = .32$ = .10, with significantly more strategies used after training than before on both tasks. Self-efficacy also showed significant linear increases from week 1 to week 9, $F(1, 135) = 30.2$, $p < .001$, $\eta_p^2 = .32$ = .18, as did the MIA locus of control scale, $F(1, 135) = 39.8$, $p < .001$, $\eta_p^2 = .32$ = .35 (see Table 1).

Model Testing

A latent growth curve model was developed using individual differences (age, education, health rating), information processing (strategy usage) and self-regulatory factors (locus of control, self-efficacy) to predict baseline memory performance and training-related memory gains. In addition to the prediction of gains, other paths were included in the model based on past research. It was hypothesized that baseline memory self-efficacy would be predicted by years of education and self-reported health (Hertzog, Lineweaver, & McGuire, 1999; Shaw & Krause, 2001), but not by age (with no younger adults in the sample). Active engagement should be predicted by education, self-efficacy and health (Bag-well & West, 2008) and baseline ability—as those who did well at baseline are more likely to have effective information processing skills to activate as they invest effort to learn from training. The model used in the initial analyses is shown in Figure 2.

For each of the variables that showed change due to training—strategies, memory self-efficacy, and memory locus of control (Hastings & West, 2009; West et al., 2008)—we created a separate latent growth curve model to predict memory performance change, using name recall and text recall measures in separate analyses. The model was tested allowing for free estimation of the week 5 and week 9 path coefficients on recall, allowing the actual data to determine the pattern of growth as opposed to imposing a linear or quadratic constraint on the shape of the memory change over time (Ram & Grimm, 2007). Following the typical procedure, each assessment (1, 5, and 9) was specified to load equally on the intercept. Thus, in this model, the slope for performance represented memory gains over nine weeks and the intercept represented general memory capability. For ease of reading, the general terms "memory," "self-efficacy," or "strategy usage" will refer to the intercept variables and slope variables will be referred to using the words "change," "gain," or "growth." An intent-to-treat approach was employed, using maximum likelihood estimation in AMOS for missing values, to ensure that all participants were represented in the data.

The model presented in Figure 2 was the starting point for testing separate models for predicting growth for name recall and for text recall. Paths that were not significant for *both* the name data and the text data were trimmed, yielding the model shown in Figure 3. According to Hu & Bentler (1999), the following criteria represent adequate fit: nonsignificant Model χ^2, CFI ≥ .95, and RMSEA ≤ .06. Measurement models were examined to confirm the basic structural relationships in the models. These showed acceptable fit with CFI > .95, strong loadings of indicators on latent intercept variables (from .62 to .91), and moderate slope loadings that ranged from .24 to .31. Sobel tests were utilized to examine the indirect effects in the models (Preacher & Leonardetti, 2006).

Text Recall

With self-efficacy intercept and slope as predictors, the trimmed latent growth curve model pictured in Figure 3 showed good fit for text recall: $\chi^2(24) = 27.464$, $p = .28$, CFI = .99, RMSEA = .03(range = .00-.08), PCLOSE = .674. Table 2 shows the univariate correlations and standardized coefficients for these two models are provided in Figure 3.[2] Younger individuals had higher performance, and healthier and more educated individuals had higher self-efficacy, and those with higher self-efficacy performed better overall and showed greater change in memory. Health and memory had a significant effect on active engagement. In addition to its direct effect on self-efficacy, education had an indirect effect on memory ($\beta = .24$, $p < .05$), as did health ($\beta = -.13$, $p < .05$). Active engagement was indirectly affected by age ($\beta = -.11$, $p < .01$). No other indirect effects were significant.

One important possibility to explore is that self-efficacy operates on performance by leading to increased strategy usage. To examine this possibility, we tested an expanded model in which self-efficacy and strategy usage both affected performance with self-efficacy predicting strategy usage. The model is shown in Figure 4 (with coefficients for name recall). For text recall, this combined strategy-self-efficacy model showed weak but acceptable fit, $\chi^2(49) = 69.1$, $p < .05$, CFI = .96, RMSEA = .06 (range = .02-.08), PCLOSE = .370. Self-efficacy predicted strategies ($\beta = .25$, $p < .05$) and memory gain ($\beta = .83$, $p < .05$), but strategies did not significantly predict memory gain ($p > .10$). To further investigate the role of strategies and self-efficacy as selfregulatory variables, the model in Figure 4 was compared to two alternate models—one without self-efficacy and one without strategies—using nested model comparisons. Without strategy included (basically, a return to the model presented in Figure 3 in which self-efficacy is the primary predictor), there was a significant improvement in model fit, $\chi^2(25) = 41.6$, $p < .05$. Without self-efficacy, and leaving only strategy change as a predictor of memory change, fit was not acceptable, $\chi^2(35) = 73.8$, $p < .001$, CFI = .89, RMSEA = .09 (range = .06–.12), PCLOSE = .01. Thus, a model predicting memory change from strategy change alone is not acceptable, and nested model comparisons of Figure 3 and Figure 4 models indicate that the model presented in Figure 3 shows the best fit for modeling intervention outcomes.

Other Models

Substituting locus of control intercept and slope as the predictor variables, the intercept did not predict baseline memory ($p > .31$) and change in locus did not predict memory change ($p > .50$) although overall fit was acceptable, $\chi^2(23) = 25.24$, $p = .338$, CFI = .993, RMSEA = .027, PCLOSE = .718.

Finally, to ensure that self-efficacy was not simply a stand-in for active engagement, we removed self-efficacy from the model and retained active engagement as a predictor of memory gain, with baseline memory predicting engagement. This resulted in a significant chi square, and unacceptable fit, $\chi^2(12) = 23.3$, $p = .025$, CFI = .959, RMSEA = .084, PCLOSE = .129. Active engagement did not predict memory gain ($p > .50$).

Because the model was exploratory, we considered it important to run some additional tests to ensure that our model using self-efficacy was the best way to capture these data. Paths that were not predicted in our initial model were examined to determine whether the addition of these other paths would improve or change the model. First, we added paths to the Figure 3 model: from self-rated health to memory gain, from age to active engagement, age to memory gain, and age to self-efficacy. We also tested the value of adding additional paths to predict self-efficacy change from health, age, and education. None of these paths were significant.

Finally, we examined the influence of other factors at baseline, including mental speed, vocabulary, and MIA subscales as predictors of baseline scores and gain. Each of these variables was added individually to the model to assess their predictive value. None of these were significant predictors.

Name Recall

The models shown in Figures 3 and 4 were verified by examining the name recall data. The latent growth curve model pictured in Figure 3 showed good fit for name recall, $\chi^2(24) = 19.6$, $p = .45$, CFI = 1.0, RMSEA = .01 (range = .00-.06), PCLOSE = .84. Standardized coefficients for this model are shown in Figure 3. Unlike text recall, there was no significant direct prediction of memory change by self-efficacy change and there was a significant prediction of self-efficacy change by active engagement. Consistent with the text recall model, younger individuals had higher performance, and healthier and more educated individuals had higher self-efficacy, and those with higher self-efficacy performed better overall. Health and memory had a significant effect on active engagement. In addition to its direct effect on self-efficacy, education had a significant indirect effect on name memory ($\beta = .18$, $p < .01$) through influence on self-efficacy, as did health ($\beta = -.09$, $p < .05$). The indirect effect of active engagement on memory change was not significant ($\beta = .22$, $p > .10$).

Name recall data was also evaluated with the model in Figure 4, which showed very good fit, $\chi^2(49) = 50.3$, $p = .35$, CFI = .99, RMSEA = .02 (range = .00-.06), PCLOSE = .844. In this model, self-efficacy predicted strategies ($\beta = .24$, $p < .05$) and strategies approached significance in predicting memory gain ($\beta = .60$, $p < .10$), but self-efficacy did not directly predict memory gain ($p > .10$). In addition to its direct effect on self-efficacy, education had a significant indirect effect on name memory ($\beta = .18$, $p < .05$) through its influence on self-efficacy, as did health ($\beta = -.08$, $p < .05$). Indirect effects of active engagement on memory gain via self-efficacy change ($\beta = .10$) or strategy change ($\beta = .15$) were not significant.

To further investigate the relative predictive power of strategies and self-efficacy as self-regulatory variables, the model in Figure 4 was compared to two alternate models—one without self-efficacy and one without strategies—using nested model comparisons. Leaving only strategy change as a predictor of memory change, fit was not acceptable, $\chi^2(35) = 55.8$, $p < .01$, CFI = .95, RMSEA = .07 (range = .03-.10), PCLOSE = .16, confirming the results for text recall showing that strategy change alone provides poor prediction of memory outcomes. Nested model comparisons of the two acceptable Figure 3 and Figure 4 models for name recall showed no significant difference between the Figure 4 model for name recall and the Figure 3 model, $\chi^2(25) = 30.4$, $p = .25$. Unlike the results for text recall, these two models are comparable in fit, that is, inclusion of self-efficacy and strategies together as predictors is no different from a more parsimonious model including self-efficacy alone.

Other Models

Exploratory models used for text recall were again examined, modeling the impact of locus of control in place of self-efficacy as a predictor, adding new paths to test (see text recall description above), or adding in baseline scores as additional predictors for the primary model. None of these analyses revealed any significant findings. In contrast to text recall, however, the model with active engagement alone was of some interest. As before, we removed self-efficacy from the model and retained active engagement as a predictor of memory gain, with baseline memory predicting engagement. This resulted in a significant chi square, and unacceptable fit, $\chi^2(11) = 21.7$, $p = .027$, CFI = .971, RMSEA = .085(.03-.14), PCLOSE = .127; however, active engagement did significantly predict memory gain ($\beta = .34$, $p < .05$).

Discussion

Over the last two decades, considerable success has been found with comprehensive group training programs (Ball et al., 2002; Floyd & Scogin, 1997; Rebok et al., 2007; Verhaeghen et al., 1992). In addition to demonstrating that interventions can lead to improved memory, it is also important to learn what factors influence training gains, in order to tailor programs so that they may have their greatest possible effect (Kliegl et al., 1990; Verhaeghen et al., 1992). Our approach to this issue emphasized that successful training outcomes depend on self-regulation, that is, the extent which individuals applied themselves in terms of information processing (e.g., increased strategy usage) and adaptive beliefs (e.g., increased locus of control). The impact of potential individual differences was also assessed. The model examined in this paper attempted to use a time-varying covariate to understand mechanisms for training gain in a performance growth pattern that included both improvement (from week 1 to week 5) and maintenance (through week 9).

The current study is the first, to our knowledge, to assess training-related gains for memory using a multivariate latent growth curve model. The evidence demonstrated that self-efficacy predicted performance for both variables, and that self-efficacy change showed the best relationship to memory change for text recall. For name recall, a model including both strategies and self-efficacy as predictors showed excellent fit to the data, as did a model using self-efficacy variables only.

Within a fairly broad age range, from 50s to 90s, communitydwelling individuals showed significant training benefits. In the model proposed here, individual difference factors such as education, health, and age were expected to influence training outcomes, along with changing memory self-efficacy and active engagement in training. The results indicated that education and health influenced level of self-efficacy, and age influenced baseline memory, but none of these individual difference factors predicted performance growth or self-efficacy growth during training. This finding is encouraging, as it suggests that less educated older adults in poorer health, who started at a lower performance baseline, may still benefit from training.

Many authors have emphasized the theoretical importance of self-regulatory factors for training-related improvement (Bissig & Lustig, 2007; Lachman et al., 1992; Rebok & Balcerak, 1989; Valentijn et al., 2005). These findings on the direct impact of memory self-efficacy on performance and on performance change underscore the influence of self-efficacy. Low memory self-efficacy could undermine future potential for memory improvement (Valentijn et al., 2006; Welch & West, 1995) and may be an important variable to target in comprehensive memory interventions (Rapp, Brenes, & Marsh, 2002; Schmidt, Berg, & Deelman, 2000; West, Welch, & Yassuda, 2000; Woolverton, Scogin, Shackelford, & Black, 2001). It is interesting that the impact of self-efficacy on overall performance was significant for both name recall and text recall, but for memory change, self-efficacy had a significant direct impact only for the text recall data. For name recall, active engagement appeared to play a more important role. With both outcome variables, these self-regulatory variables were more prominent predictors than strategy usage. It is possible that this result may not generalize to other intervention approaches, as this training program was specifically designed to change self-efficacy and encourage engaged effort. One thing to note—given the possible reciprocal influences between self-regulation and test performance—it is impossible to rule out an alternative interpretation, that is, that improvements in memory performance led to self-efficacy change or more active engagement. However, we believe that it is more likely that these self-regulatory variables were driving the change, given the self-regulatory elements in this training program, and previous theoretical work emphasizing the role of self-regulatory variables in cognition (Bandura, 1997; Stine-Morrow et al., 2006a).

The present analysis does not fully explain why there were differences between the two outcome variables in these models. Comparisons between text training strategies and name training strategies, although speculative, may be useful in thinking about these differences. Both strategies required multiple steps for successful utilization but the steps in the PQRST method for text recall may have been easier to apply. The PQRST (Preview, Question, Read, Summarize, Test) strategy for text recall is similar to speed-reading approaches and the well-known SQ3R method (Survey, Question, Read, Recite, Review). Thus, with a strategic approach that was relatively well known and easy to use, it may be that early successes with training raised self-efficacy, and led over the course of the intervention to significant text recall change, whether or not the individual maintained active engagement throughout the intervention. In contrast, the image-name-matchmethod (West, 1995), which was the focus of name recall training, is relatively unknown, involving challenging steps such as developing a concrete object that represents the name, and developing a facial image with that concrete object exaggerated. Early efforts to apply the strategy may have been less successful. It could be the case, then, that only those participants who were actively engaged throughout the training were able to improve their name recall. To test this hypothesis, it would be fruitful to assess self-efficacy and performance at each training session to provide a more detailed examination of the trajectories of change in both factors. Given that no single variable showed a significant prediction of name recall change in the models, it is likely that some nonmeasured factors may also have contributed to name recall gains (e.g., imagery production skill, visual memory, persistence).

It is interesting that, considering all of these factors together, active participation in training did not have a significant effect on memory change, although it had shown a significant effect in other research (Bagwell & West, 2008). In that study, however, static scores were evaluated in univariate tests, without examining a multivariate growth curve model. Here, active engagement was not, by itself, a critical factor explaining training outcomes in the models that fit the data overall, although it did show a strong relationship to memory change in a model that, overall, showed poor fit. Instead, active engagement was influenced directly by health and overall performance (which was predicted significantly by age and overall self-efficacy), was indirectly influenced by age (through its impact on performance), and had a direct impact on self-efficacy change. Given these results, it would be premature to conclude that active engagement in training is unimportant to performance growth. In the model proposed in this paper, active engagement was based on trainers' assessment of factors like class involvement, homework and attendance. Attendance may have been related to transient health problems. Cognitive status may have affected homework completion or ability to ask effective questions in class. Thus, this active engagement variable, although partially related to motivation, clearly was affected also by factors other than intrinsic motivation or willingness to work hard. It might be interesting for future research to examine measures of internal motivation directly to further understand the role of motivated effort in intervention outcomes.

Interestingly, there was a training-related increase in number of strategies employed, but model fit was not better when strategies were included in the model without self-efficacy, and in the case of text recall, model fit was significantly worse with strategies and not self-efficacy in the model. It could be that strategy usage would predict gains better if we identified participants who focused on using the best possible strategy, however, few participants used that approach (see West et al., 2008). Similarly, locus of control significantly improved with training but did not predict training-related gains in memory. It may be that the process of gaining some new memory strategies made trainees feel like they had more control over their memory performance, but that individual differences in skill levels or willingness to employ the most effective strategies led to variations in the relationship between control and performance outcomes. More on-task analyses, perhaps asking individuals about their strategy choices during study time, might be useful to explore this notion.

As is common with intervention studies, there were participants who discontinued training and, therefore, had missing values for some of their scores. An intent-to-treat approach was used, ensuring that all participants enrolled in the study were represented in the final sample, using maximum likelihood estimates to account for missing scores. A previous analysis of attrition for this training program found that the only variable significantly related to attrition was participant age, with younger individuals more likely to withdraw than older individuals (West et al., 2008), perhaps due to work responsibilities for those in their 50s. It is encouraging that baseline ability did not affect attrition and that older adults tended to stay in the training program to gain the benefits from the intervention.

An additional limitation is that the model only included two measurements of memory self-efficacy. Having only two occasions of measurement does not allow for examination of the shape of the memory self-efficacy trajectory or rate of change (Duncan, Duncan, & Strycker, 2006; Rogosa, 1995). These models do not permit analysis of whether memory self-efficacy change leveled-off between weeks 5 and 9, because they necessitate an assumption that growth occurred in a linear way (Duncan et al., 2006; Rogosa, Brandt, & Zimowski, 1982). However, two occasions of measurement are considered sufficient to estimate overall amount of change (Duncan et al., 2006; Rogosa, 1995), and a model treating the two self-efficacy measures as separate indicators also showed good fit.

In this research, neither age nor education nor health, as individual differences, predicted gains during training, although education and age affected gains indirectly, by influencing overall scores. Future research should delve into other individual-differences variables that may impact training gains, such as personality factors or intrinsic motivation. It would also be interesting to test latent growth curve models for various types of training (such as media-based training in the home via CD-ROM, or manualized self-help training) in order to identify whether these types of training show differing predictors of training gain. Not surprisingly, those with the highest overall score and the best health were the most active trainees, and those who had the highest self-efficacy performed best overall. The most important factor related to training gains in this study were self-regulatory factors. The most self-efficacious individuals had the highest scores and showed the greatest gains in text recall. For name recall, self-efficacy and active engagement both had some indirect influence on change, but additional unmeasured factors could also be important and need to be considered in the future. Overall, these results underscore the potential of targeting and testing the impact of self-regulatory factors in intervention programs designed to improve memory skills.

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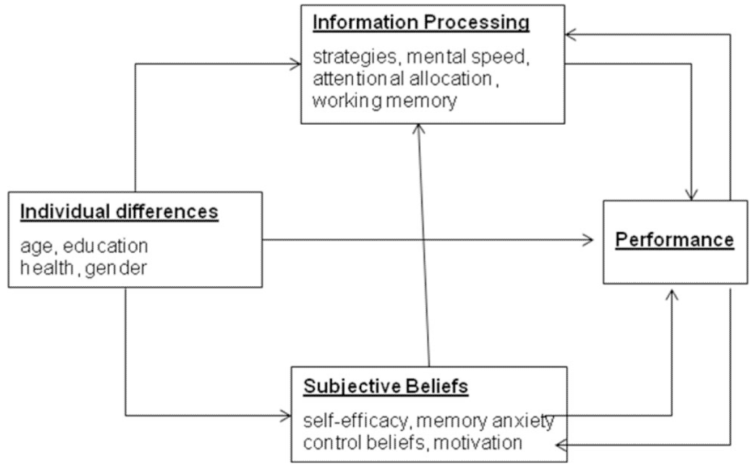

Figure 1.
Relationships among variables from a self-regulation perspective.

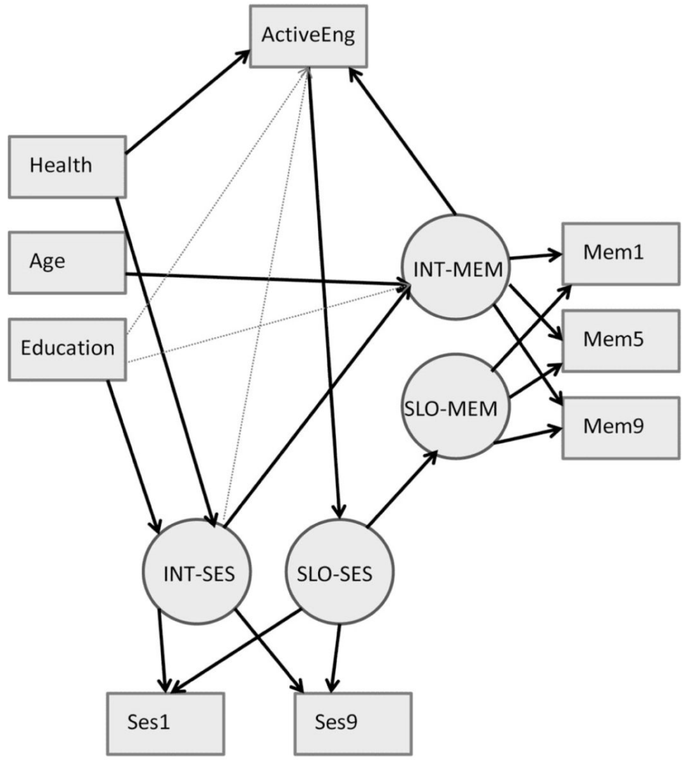

Figure 2.

Hypothesized model. Dashed pathways were trimmed, due to nonsignificance in models for both text recall and name recall. ActiveEng = active engagement; INT-MEM = intercept for memory; INT-SES = intercept for self-efficacy; SLO-MEM = slope for memory gain; SLO-SES = slope for self-efficacy gain. Ses1 and Ses9 are self-efficacy scores for week 1 and week 9, respectively. Mem1, Mem5, and Mem9 are memory test scores for week 1, week 5, and week 9, respectively.

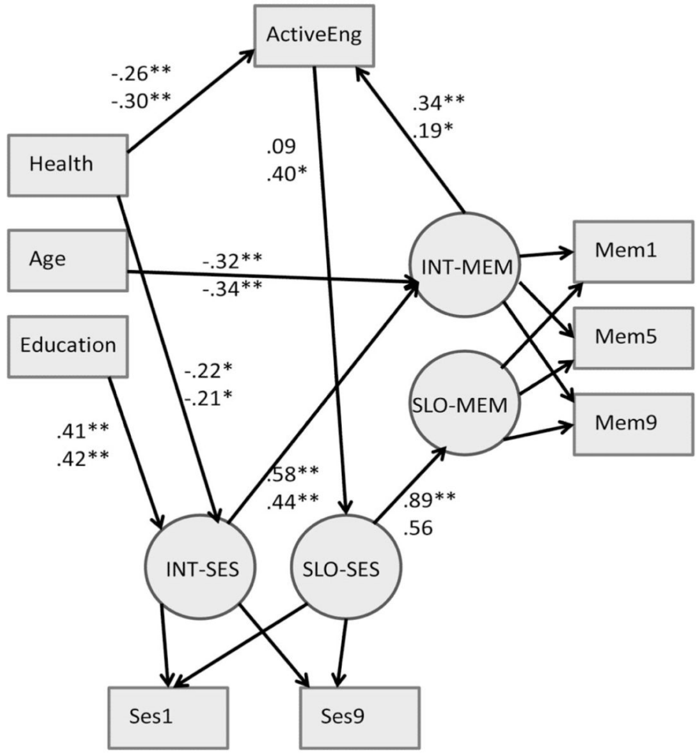

Figure 3.

Model verified with text recall and name recall intervention outcome data. ActiveEng = active engagement; INT-MEM = intercept for memory; INT-SES = intercept for self-efficacy; SLO-MEM = slope for memory gain; SLO-SES = slope for self-efficacy gain. Ses1 and Ses9 are self-efficacy scores for week 1 and week 9, respectively. Mem1, Mem5, and Mem9 are memory test scores for week 1, week 5, and week 9, respectively. The top standardized coefficient is for the text recall data and the bottom number is for the name recall data. *$p < .05$. **$p < .001$.

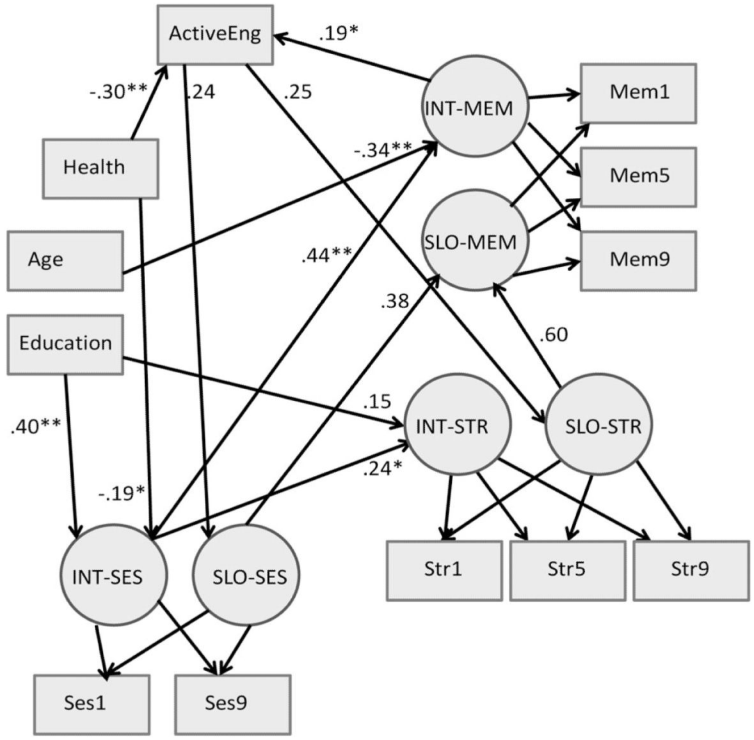

Figure 4.

Model tested with both strategy change and self-efficacy change as predictors of memory gain. ActiveEng = active engagement; INT-MEM = intercept for memory; INT-SES = intercept for self-efficacy; INT-STR = intercept for strategy use; SLO-MEM = slope for memory gain; SLO-SES = slope for self-efficacy gain; SLO-STR = slope for gain in strategy usage. Ses1 and Ses9 are self-efficacy scores for week 1 and week 9, respectively. Str1, Str5, and Str9 are name recall strategy scores for week 1, week 5, and week 9, respectively. Mem1, Mem5, and Mem9 are name recall test scores for week 1, week 5, and week 9, respectively. This model showed strong fit to the name recall data as reported here. *$p < .05$. **$p < .001$.

Table 1

Means and Standard Deviations (In Parenthesis) For Key Variables

Variable	Week 1	Week 5	Week 9
Text recall	.41 (.12)	.49 (.12)	.49 (.12)
Name recall	10.44 (5.4)	12.78 (5.7)	13.09 (5.8)
Text Strategies	4.84 (1.75)	5.24 (1.89)	5.53 (1.81)
Name Strategies	4.25 (1.87)	5.12 (2.36)	5.45 (2.52)
Locus of Control	3.81 (.40)	—	4.05 (.37)
Memory Self-Efficacy	46.28 (15.57)	—	52.16(13.93)
Age	70.51 (7.69)	—	—
Health	3.00 (1.57)	—	—
Years of Education	15.39 (2.98)	—	—

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Table 2

Correlations Among Model Variables

	Text recall (Wk 1)	Text recall (Wk 5)	Text recall (Wk 9)	Strategy Use (Wk 1)	Strategy Use (Wk 5)	Strategy Use (Wk 9)	Locus of Control (Wk 1)	Locus of Control (Wk 9)	Memory Self-Eff. (Wk 1)	Memory Self-Eff. (Wk 9)	Age	Health	Education
Text recall (Wk 5)	.61**												
Text recall (Wk 9)	.62**	.78**											
Strategy Use (Wk 1)	.25**	.00	.04										
Strategy Use (Wk 5)	.09	.16	.08	.49**									
Strategy Use (Wk 9)	.11	.19*	.18*	.35**	.45**								
Locus-Control (Wk 1)	.15	.14	.12	.04	.00	.01							
Locus-Control (Wk 9)	.14	.16	.15	−.11	−.02	.12	.49**						
Memory Self-Eff. (Wk 1)	.42**	.34**	.34**	.15	.12	.10	.10	.05					
Memory Self-Eff. (Wk 9)	.33**	.38**	.43**	.05	.07	.24**	.11	.21*	.65**				
Age	−.27**	−.41**	−.40**	.00	−.05	−.16	−.24**	−.22**	−.16	−.13			
Health	−.20*	−.22**	−.23**	−.08	−.04	−.10	−.16	−.21*	−.24**	−.26**	.14		
Education	.38*	.30*	.32**	.13	.13	.18*	.06	.15	.36**	.42**	−.20*	−.15	
Active Engagement	.34**	.35**	.37**	.16	.24**	.20*	.12	.14	.22*	.29**	−.27**	−.34**	.21*