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INDIVIDUAL DIFFERENCES IN TASK-SPECIFIC PAIRED ASSOCIATES LEARNING IN OLDER ADULTS: THE ROLE OF PROCESSING SPEED AND WORKING MEMORY

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Abstract

Background—The role of processing speed and working memory was investigated in terms of individual differences in task-specific paired associates learning in a sample of older adults. Task-specific learning, as distinct from content-oriented item-specific learning, refers to gains in performance due to repeated practice on a learning task in which the to-be-learned material changes over trials.

Methods—Learning trajectories were modeled within an intensive repeated-measures design based on participants obtained from an opt-in internet-based sampling service ($M_{\text{age}} = 65.3$, $SD = 4.81$). Participants completed an eight-item paired associates task daily over a seven-day period.

Results—Results indicated that a three-parameter hyperbolic model (i.e., initial level, learning rate, and asymptotic performance) best described learning trajectory. After controlling for age-related effects, both higher working memory and higher processing speed had a positive effect on all three learning parameters.

Conclusion—These results emphasize the role of cognitive abilities for individual differences in task-specific learning of older adults.

Previous research on paired-associate (PA) learning demonstrated that there is an age-related decline in performance, especially for semantically non-related word pairs (Naveh-Benjamin, 2000; Old & Naveh-Benjamin, 2008). Explanations for this age-related decline include age deficits in associative memory (Kausler, 1994; Naveh-Benjamin, 2000), (temporal) item-context binding (Kahana, Howard, Zaromb, & Wingfield, 2002; Probyn, Sliwinski, & Howard, 2007), and strategy use (Dunlosky & Hertzog, 1998; Verhaeghen & Marcoen, 1994). Notably, nearly all studies on PA learning of older adults have focused on item-specific PA learning, that is, learning of some specific to-be-learned material, for example, learning of the word pair *pencil-flower* over several trials. By contrast, the present

study investigated task-specific PA learning. By the term task-specific PA learning we refer to gains in performance due to repeated practice on a learning task---irrespective of the to-be-learned material. This type of learning can be achieved by mere repetition of the same task with the material presented in the task changing over trials. The goal of the present study was to quantify the amount of this task-specific learning in older adults, to examine individual differences in such learning, and to investigate the role of cognitive abilities in accounting for these individual differences.

Task-specific Learning

Repetition of study trials and subsequent recall trials is, in addition to strategy use (Rogers & Gilbert, 1997) and item spacing (Cepeda, Pashler, Vul, & Wixted, 2006; Donovan & Radosevich, 1999; Peterson, Wampler, Kirkpatrick, & Saltzman, 1963), a key component of verbal learning (Karpicke & Roediger, 2007). However, note that repetition may refer to content repetition or task repetition. Item-specific learning involves content repetition, and refers to gains in performance associated with the repeated presentation of the identical to-be-learned material over several trials. Task-specific learning involves repetition of the task (i.e., demands, duration, procedure of the task) but with different sets of to-be-learned material. Thus, content repetition requires task repetition, but not vice versa. In the case of PA learning, task-specific learning could be examined by presenting different sets of word pairs in every learning trial and measuring performance changes over trials. Thus, the task requires a participant to associate cue and target stimuli and to recall the target stimuli when prompted with the cue. However, because the corresponding word pairs vary from trial to trial, there is no overlap regarding the to-be-learned material. As will be argued in the following, such repetition of the same type of task may result in increasing mastery of the type of task (i.e., task-specific learning) as indicated by performance gains from trial to trial.

The distinction between item-specific vs. task-specific learning implies a distinction between two different effects of learning occurring in the same task: Learning due to the repetition of the to-be-learned material or learning due to the type of task alone. With regard to multi-trial PA tasks, learning may be decomposed into the two effects mentioned: learning due to repetition of the content (item-specific learning) as well as due to repetition of the task demands (task-specific learning). For example, Rast and Zimprich (2009) took into account the beneficial effect of multiple study and retrieval trials (Grimaldi & Karpicke, 2012; Karpicke & Blunt, 2011; Karpicke & Roediger, 2007, 2008; Pyc & Rawson, 2009) by using a multi-trial PA task to investigate individual differences in PA learning of older adults. Nevertheless, it remains an open issue of how large the contribution of each type of effect is. Learning may be due to repetition of the content (item-specific learning) as well as due to repetition of the task demands (task-specific learning). To quantify the effect of task-specific learning, the present study used a multi-trial PA task with the to-be-learned material changing over trials.

Task-specific learning as described above has been an issue in memory research for a long time, albeit such learning processes have been called learning to learn, or nonspecific learning (Gorfein & Viviani, 1978; Hultsch, 1974; Moely & Shapiro, 1971; Schwenn & Postman, 1967). Central to this research is the question of why repeating task procedures though changing to-be-learned material results in performance gains. Schwenn and Postman (1967) suggested that task-specific learning occurs because of “the development of instrumental habits that facilitate the acquisition of prescribed verbal associations, e.g., the use of coding devices and mediators” (p. 565). Accordingly, task-specific PA learning might include an alteration in the way and the strength with which associations between cues and targets are formed. Schwenn and Postman (1967) presented a list of word pairs either 4 or 10 times (only study trials). Afterwards, a new, critical list of word pairs was presented. The

authors showed that more learning trials (10 versus 4) of the same type of a PA task led to better performance in recalling the critical list of word pairs. Thus, the learning curve for subjects who had received 10 trials prior to the final test was characterized by a faster learning rate and a higher maximal performance. These results indicate that the type of task and the demands involved had been learned in ways that were unrelated to the to-be-learned material. Thus, it appears as if participants had acquired task-specific skills that enhanced the readiness to form associations in the to-be-learned material, which could have resulted to more time being available for rehearsing cues and targets (Schwenn & Postman, 1967). These increases in performance may refer to non-specific warm-up effects and other learning effects, e.g., strategy use which is content independent or increased familiarity with task procedures and demands. This increased familiarity with the type of task can free up attentional resources to devote to performance, e.g., rehearsal processes (Baumeister & Maisto, 1974).

Apart from learning-to-learn studies, studies on interim test effects provide a further approach that is related to task-specific learning (Rogers & Gilbert, 1997; Szpunar, McDermott, & Roediger, 2008; Wissman, Rawson, & Pyc, 2011). Interim test effects refer to the benefits of repeated testing for subsequent performance in recalling new verbal material. Whereas many studies focused on item-specific interim test effects, recently, interim test effects have also been investigated in terms of task-specificity (Szpunar et al., 2008; Wissman et al., 2011). For example, Wissman et al. (2011) presented unrelated stories. In one group, the interim-test group, participants recalled the first part of the story after reading it. The other group read the story without any interim recall test. Following this, all participants were asked to recall the last part of the story. Thus, participants in the interim group received a study and a test trial of different to-be-learned material (first part of story) prior to study and recall of the second part of the story. Results indicated that participants in the interim-test group showed a better recall performance than participants in the no-interim test group. Explanations for such a task-specific interim testing effect are, for example, a facilitated comprehension of subsequent text material due to a higher accessibility of prior information (cf. Wissman et al., 2011), an increased use of effective encoding strategies (cf. Wissman et al., 2011), or a better discrimination of words and their corresponding belongingness to different lists (cf. Szpunar et al., 2008). Wissman et al. (2011) argued that a retrieval attempt of previous to-be-learned material and the realization that retrieving is difficult might enhance the use of effective encoding strategies during subsequent learning trials, which would result in improvements in performance over trials---even if the to-be-learned material changes from trial to trial. Such enhancements in encoding strategies use should be reflected in task-specific learning trajectories, thus, in performance gains because skills that are required for the type of task are enhanced and subsequent learning becomes easier.

Note, however, that previous studies of interim effects have focused on group differences in recall performance between interim test vs. no interim test conditions. In extending this type of research, the question of the present study was not only whether there are individual differences in benefitting of interim tests, but rather whether recall performance continues to increase over several interim tests. More specifically, as with other types of learning, one might expect that recall performance increases across trials, but with diminishing returns, thus resulting in non-linear task-specific learning curves. Furthermore, whereas interim tests usually took place over short intervals, the present study focused on the preservation of benefits that might be reflected in task-specific learning curves over days (Newell, Liu, & Mayer-Kress, 2001). Timescales in learning studies may refer basically to two different time scales of learning: Persistent (long-term) and transitory (short-term) learning (Newell et al., 2001). Transitory learning refers to changes in performances, which may fluctuate over learning sessions. In contrast, persistent learning means slow and durable performance gains

over longer time intervals. Note that Newell et al. (2001) primarily focused on multiple time scales in motor learning, however, the authors also emphasized that any human learning may be composed of those multiple time scales. Thus, item-specific and task-specific PA learning can be described as transitory or persistent learning, respectively. As the aim of the present study was to analyze performance gains across trials with changing material, in terms by Newell et al. (2001), a persistent learning condition of task-specific learning was implemented.

Predictors of Individual Differences in Task-Specific Paired Associates Learning of Older Adults

In the field of research on item-specific verbal learning, recently, the focus has been complemented by the examination of individual differences in learning (Kyllonen, Tirre, & Christal, 1991; Rast & Zimprich, 2009; Rast & Zimprich, 2010; Zhang, Davis, Salthouse, & Tucker-Drob, 2007; Zimprich, Rast, & Martin, 2008). Note that individual differences in learning may contribute to different characteristics of the learning curve. With regard to episodic memory (Rast, 2011; Zimprich et al., 2008) and item-specific paired associates learning (Rast & Zimprich, 2009), learning and individual differences therein have been described by a model comprising three parameters: initial level of learning, learning rate, and asymptotic performance (cf. Meredith & Tisak, 1990).

When individual differences in these three learning parameters are modeled, a naturally occurring subsequent question is whether there are characteristics of the individual which may explain these individual differences. Those studies focusing on predictors of individual differences in item-specific verbal learning provided evidence that basic cognitive abilities such as working memory and processing speed account for individual differences in learning of older adults (Hertzog, Dixon, Hultsch, & MacDonald, 2003; Rast, 2011; Zimprich et al., 2008). For example, faster processing speed was related to a faster learning rate (Rast & Zimprich, 2009). Basic cognitive abilities, such as working memory and processing speed, may influence individual differences in item-specific verbal learning because of their involvement in both encoding and retrieval (Salthouse, 1996; Unsworth & Engle, 2007). Accordingly, the present study investigated whether the associations also exist between learning parameters in task-specific PA learning trials and basic cognitive abilities in older adults. How might working memory and processing speed affect task-specific learning? Unsworth and Engle (2007) suggested a framework in which individual differences in working memory were related to retrieval processes. The authors argued that depending on the successful use of cues, which delimit the size of the search set as suggested by random search models (Raaijmakers & Shiffrin, 1981), the search set at retrieval might be larger or smaller. If the search set is smaller and contains only or mainly relevant information, retrieval may be facilitated. Individuals with lower working memory capacity may execute the search process less effectively because of a poorer use of cues or because they rely on noisier context cues, which may result in lower recall performance (Unsworth, 2007; Unsworth & Engle, 2007; Unsworth, Brewer, & Spillers, 2011).

Regarding processing speed, Salthouse (1996) proposed two mechanisms, which may help explain individual differences in task-specific PA learning of older adults due to lower processing speed: The limited time and the simultaneity mechanism. Due to lower processing speed a limited mechanism sets in that is characterized by cancelling ongoing elementary operations because of an internal lack of time. Additionally, a simultaneity mechanism sets in, which impedes the availability of previous executed operations and their products and thus, leads to less information activated that is requested for other processes (Salthouse, 1996). As the mechanisms of working memory and processing speed have been evaluated primarily in terms of item-specific learning, the present study extends this

investigation of the role of working memory and processing speed to task-specific PA learning. As in item-specific learning, we expect that working memory and processing speed are fundamental components to complex learning skills, including task-specific learning effects.

Aims of the Present Study

The overarching goal of the present study was to investigate individual differences in task-specific PA learning in older adults. The analysis of the present study comprised two steps. In a first set of analyses, we examined whether task-specific PA learning trajectories of older adults could be described by three parameters, each reflecting a different characteristic of learning, namely, initial level, learning rate, and asymptotic performance as indicated by prior studies regarding item-specific PA learning over minutes (Rast & Zimprich, 2009). To do so, we investigated whether any of three non-linear functions captured task-specific PA learning best. More specifically, we examined the exponential curve (e.g., Heathcote, Brown, & Mewhort, 2000), the hyperbolic curve (e.g., Mazur & Hastie, 1978), and the power curve (e.g., Logan, 1988). As a standard of comparison, we also examined a linear and quadratic curve model. In a second set of analysis, we investigated whether there are relations between basic cognitive abilities and task-specific PA learning trajectory parameters of older adults. To do so, we included between-person differences in processing speed and working memory as predictors of the three learning curve parameters, adjusted for age-related differences in learning.

Method

Participants

Participants in the current study were $N = 65$ participants recruited from an opt-in internet-based sampling service (StudyResponse) hosted at Syracuse University. Both StudyResponse and the current study received approval from the Syracuse University Institutional Review Board. Participants were on average 65.3 years of age ($SD = 4.81$; range 56-74 years) and had 14.2 years of education ($SD = 3.55$). Fifty-six individuals (95%) self-identified as white/Caucasian (1 as African-American; 2 as Other; and 6 with missing demographic data). Participants rated themselves as in good health on the five-point general health item of the SF-36 ($M = 3.20$, $SD = .96$; Turner-Bowker, Bartley, & Ware, 2002).

Procedure

An initial sample of participants was generated through a pre-screening survey by an opt-in online research service (StudyResponse). Participants saw an ad for the service on several websites. After signing up to the service participants were asked about interest and willingness to complete an eight-day daily diary study. Four hundred and seven individuals between the ages of 55 and 75 were screened and, of those, 236 (58%) indicated they were interested. From these individuals, a random sample of 50 young-old (ages 55-65) and 50 old-old (ages 66-74) stratified by gender were sent invitations to the current study. The random sample of the 100 participants was slightly older than the sample of the 236 participants ($t[234] = -4.93$, $p < .01$) because we specifically included proportionally more old-old participants than were registered (50% selected vs. 21% registered). Similarly, there were also slightly more males ($\chi^2[1] = 4.13$, $p = .04$) again due to specific sampling for equal numbers of men and women in the random sample of the 100 participants. The sample of the 236 participants who were willing and interested in participating did not differ from the current sample ($N = 65$) regarding gender ($\chi^2[1] = .53$, $p = .47$). The current sample was slightly older than the sample including the 236 participants ($t[234] = -2.75$, $p < .01$). The difference was about two-years. Individuals who completed the daily diary did not differ

either in age ($t[98] = .99, p = .33$) or gender composition ($\chi^2 [1] = 1.10, p = .29$) from the sample of 100 that was invited. Invited participants were provided with a link that allowed them to access the log-in page for protocol.

During the first session, which approximately lasted 30 minutes, participants provided demographic information and reported on their affect, physical health and functional limitations, perceptions of aging, personality, and life events. Participants also completed a measure of fluid intelligence during the first session. Subsequently, participants completed up to seven online sessions over the next seven days. Participants were required to wait 20 hours between each session to prevent participants from completing all sessions in a short period of time. Participants were given 10 days to complete all 8 sessions. After the 10 days participation was ended and participants were compensated for all sessions completed at that time. On average, participants completed sessions approximately 1.38 days apart ($SD = .63$). The average number of days between the first cognitive session and the last was 6.93 ($SD = 1.34$). $N = 25$ participants completed all seven sessions. Of those participants, who did not participate on all seven sessions ($N = 40$), the average number of sessions was four ($M = 4.00, SD = 1.96$). Note that there were no participants that missed a session and came back the next session.

During each of the fifteen-minute daily sessions, participants completed a variety of cognitive tasks assessing processing speed, working memory, and episodic memory. These daily cognitive tasks could, thus, be used to investigate the trajectory of task-specific learning and to examine the role of cognitive predictors for individual differences in task-specific learning, that is the individual working memory and processing speed performance. At each daily session they also completed questionnaires measuring affect, physical health, and daily stressors. Measures used in the current analyses are described below. On average, participants completed five of the seven follow up sessions with 80% of participants having completed four or more of the daily sessions.

Measures

Processing speed—Participants completed a symbol search task that assessed the speed with which they could make simple decisions. Participants saw a pair of symbols on the bottom of the screen and had to decide whether that pair was among six pairs at the top of the screen. There were 40 trials of this task. Participants could take as much time as needed. The dependent variable for this task was the number of correct answers per session. This task was repeated in every session with material changing across sessions. In order to investigate between-person differences in processing speed as a predictor of learning curve parameters, the mean performance, hence the mean of the number of correct answers per day across all sessions, was computed per individual. This score reflects the individual processing speed performance.

Working memory—Participants completed a subtract two-span task (Waters & Caplan, 2003) that assessed their ability to process information while holding it in primary memory. Participants were asked to recall a series of digits presented after subtracting two from each. Presented numbers ranged from 3-11 so that response options ranged from 1-9. Span lengths for this task ranged from 3-8 and participants attempted two trials at each span length. Score for this task was the number of items correctly recalled in the correct serial order per session. This task was repeated in every session with material changing across sessions. The mean performance, hence the mean of the number of items correctly recalled in the correct serial order per day across all sessions, was computed per individual. This score reflects the individual working memory performance.

Paired-Associate Learning—In the paired associates task, participants viewed a series of 8 word-number pairs, each presented for 1.5 seconds. The word from each pair was then presented and participants had to recall the number that was paired with that word. Study and recall trials were repeated four times for a total of 32 items per session. Items were presented in random order for both presentation and for recall trials. Trials were completed consecutively. There were no tasks in between trials within a given session. This task was repeated in every session. Word-number series varied across the daily sessions, but cue words were equated on imageability and familiarity (Friendly, Franklin, Hoffman, & Rubin, 1982). The total number of correctly recalled numbers across the four trials was the dependent variable for this task per session. Thus, seven PA scores were computed each reflecting the daily total amount of correctly recalled target items of each individual (max. 32 items).

All analyses were conducted within a mixed-effects approach using SAS PROC NLMIXED in order to fit non-linear learning curve models. The integration method was adaptive Gauss-Hermite quadrature (Pinheiro & Bates 1995). The goodness of fit of the non-nested models was evaluated by using the Akaike information criteria (AIC) and the Bayesian information criteria (BIC) indices (maximum likelihood estimation).

Results

Task-specific Learning Trajectories

Table 1 shows descriptive statistics and intercorrelations of education, age, the WM, PS, and seven daily PA scores. As expected, the means of the daily PA scores suggested a non-linear process. To verify if task-specific learning in older adults is characterized by a nonlinear trajectory, we examined in a first series of analyses, whether the exponential, power, or hyperbolic function adequately captured the performance gains in PA recall across the seven daily sessions. As a standard of comparison, we also examined a linear and quadratic curve model. The corresponding indicators for these parameters were the seven PA scores each reflecting the daily total amount of correctly recalled target items of each individual.

The first model, which described learning across seven daily sessions as a linear trajectory, captured the data compared to the next model, which comprised initial level, linear slope, and quadratic slope, less well as indicated by a higher BIC and AIC (see notes in Table 2). In a second step, an exponential, power, and hyperbolic model was fitted. As can be seen in Table 2, the hyperbolic model (Model Hyp) described the learning trajectory best as indicated by lower BIC and AIC. The fixed effects of the hyperbolic model indicated that, on average, older adults started to recall correctly eight target numbers by presenting the corresponding cue word at the end of the first day. After the seventh day, participants recalled on average twice as many target numbers (17). The learning rate parameter indicated that on average, participants improved their daily performance by recalling one additional number per day.

Significant random effects implied individual variability in all the learning parameters. Thus, participants started out at different initial levels, differed in their rate of learning, and in their asymptotic performance. In particular, individual differences in asymptotic performance and initial performance were positively related. Participants who tended to have a higher asymptote also started out at a higher learning performance.

Predictors of Task-specific Learning

Working memory and processing speed were then included as predictors of the three learning curve parameters (Model HypCog). Table 2 shows that both working memory and

processing speed were associated with the learning parameters in the same manner: Higher working memory abilities as well as higher processing speed abilities were related to a higher initial level, a faster learning rate, and a higher asymptote (see also Figure 1). Thus, older adults with relatively higher basic cognitive abilities benefit from these abilities with regard to task-specific learning. Note that all random effects remained statistically significant indicating the need for further ideas to explain why persons of older adults may differ with regard to their initial levels, learning rates, and asymptotic performances.

In order to investigate age-related effects, age was entered as a further predictor of individual differences in task-specific learning (Model HypCogAge). To account for possible effects of education and attrition on task-specific PA learning, years of education and a dummy dropout variable were included as further predictors of learning parameters in Model HypCogAge. Results of this model indicated that after adjusting for age, processing speed and working memory remained as influential predictors of all three learning parameters (see Table 2). However, note that the effect of processing speed was now related negatively to learning rate, whereas in the previous model (HypCog) this relation was positive. Age had a statistically significant effect on the initial level and asymptotic performance, with older individuals exhibiting a lower initial level and a lower asymptotic performance (see Figure 2). Regarding effects of education on task-specific PA learning, Table 2 indicates that more years of education are related to a higher asymptotic performance. The dropout indicator was related negatively to the initial level. Thus, participants that did not participate in all seven sessions recalled a lower number of word-number pairs after the first session compared with those participants who did not drop out of the study.

Each random effect was still statistically significant indicating that beyond the influence of age, education, dropout, working memory, and processing speed, there were still significant unexplained individual differences in learning parameters due to other between-person differences.

Discussion

The results of the present study demonstrate that higher basic cognitive abilities, working memory and processing speed, influenced task-specific PA learning of older adults positively even after adjusting for age-related effects on learning parameters. We used a new approach to gain insights into mechanisms of PA learning in older adults. Hence, an increase in recall performances over multiple trials with new to-be-learned material within every trial is reflective of the ability of older adults to learn the instrumental habits required for this type of learning task (Schwenn & Postman, 1967).

Results indicated that task-specific learning of older adults across seven sessions could be described by a three-parameter hyperbolic function comprising initial level, learning rate, and asymptotic performance. The present study, thus, extended existing research on item-specific “content” learning to that of task-specific learning across days (i.e., not across trials within one learning session). Note that there are studies on effects of practice in different time scales (Anderson, Fincham, & Douglass, 1999; Rickard, 2007; Sliwinski, Hoffman, & Hofer, 2010). However, these studies refer to cognitive skill learning, i.e., speedup effects, not with regard to PA learning of older adults. Thus, the present study could extend previous research on learning in different time scales by investigating individual differences in task-specific learning of verbal material across days, a time scale that has not been used in previous verbal learning tasks. Besides the mentioned discussion of persistent vs. transitory learning (Newell et al., 2001) mentioned in the introduction, research on spaced vs. massed learning (for reviews see Cepeda et al., 2006; DeJonge, Tabbers, Pecher, & Zeelenberg,

2012; Donovan & Radosovich, 1999) implies further implications for the results of present study regarding task-specific learning over days. Spaced vs. massed learning research has focused on the issue of sampling time effects of item presentation, in particular, how massed vs. spaced presentation exactly influence retention of the learned material. Most studies provide evidence that with regard to verbal learning tasks more spacing between item presentations results in a more effective and longer retention than massed presentations (Cepeda et al., 2006; Donovan & Radosovich, 1999; Janiszewski, Noel, & Sawyer, 2003; Peterson et al., 1963). To account for this spacing effect, several theoretical explanations have been forwarded including attention, rehearsal, retrieval, encoding variability, and different encoding strategies accounts (Delaney & Knowles, 2005; Janiszewski et al., 2003). In line with the distinction between massed and spaced presentation, the present study, where PA learning trials were separated by days, can be considered as invoking a spaced learning condition. As indicated by one study (Balota, Duchek, & Paullin, 1989), there is evidence that older adults benefit from spaced learning as well indicating the relevance for future research on spaced learning conditions of older adults, in particular, on learning due to repetition of task demands, and the underlying mechanisms. Furthermore, it would be interesting to investigate within and between session effects of repetition of task demands. Whereas the present study focused on between session effects, research on item-specific learning indicate that mechanisms of within and between session effects of practice, e.g., effects of forgetting, or fatigue, and gains due to consolidation processes might differ (Rickard, 2007). If those mechanisms also exist with regard to task-specific learning remains an open issue at present. Future research should focus on this issue as this is important for studies on learning of older adults, because there are likely age-related differences regarding the effects of delays (unknown periods of time) between learning sessions. The length of these periods could potentially affect the aging-related deficits found in closely spaced longitudinal studies and influence how researchers choose to space assessments in time.

The present study emphasized that individual differences in basic cognitive abilities may influence skill learning (Ackerman, 1987), or the use of task-related strategies (Cokely, Kelley, & Gilchrist, 2006). Hence, task-specific learning refers to learning skills required for the type of task that may result in a facilitated processing for subsequent learning (Schwenn & Postman, 1967; Wissman et al., 2011). Results of the present study implied that individual differences in task-specific learning were predicted by processing speed and working memory abilities: Both higher working memory and processing speed were related to a higher initial level, faster learning rate, and higher asymptote. These results imply that once task demands are learned, working memory capacity for actual items could be released as working memory capacity might be required for both the understanding and mastering demands of the type of task and the rehearsal of actual items. If one assumes that within every session a content-based (item-specific) learning process took place, working memory and processing speed could be used more efficiently for learning the specific content of the PA list of the corresponding day as there is no need for processing further task demands. To verify mechanisms of these complex relations between cognitive abilities and learning that is both content-free and content-based due to repetition of the content and repetition of task demands, future studies should analyze the effects of content and task repetition more systematically.

After adjusting for effects of processing speed and working memory on learning parameters, age had an effect on the initial level and asymptotic performance. Note that age did not moderate the effects of processing speed and working memory on the learning parameters. The non-existent influence of age on learning rate has implications for longitudinal studies as the oldest participants may benefit from task-specific learning and exposure to testing procedures to a similar degree as their younger counterparts. However, at least within the period of days as shown in the present study, older persons compared to younger persons

showed difficulty obtaining similar recall performance after seven days of task-specific PA learning.

To account for effects of possible unique properties of the web-based procedure of the present study, we include education and attrition as predictors of task-specific learning. Results indicated that participants with a higher education and participants that did not drop out also performed better in task-specific learning.

However, note that there were still individual differences in all three learning parameters. Between-person differences such as verbal knowledge, using memory strategies in daily life, or cognitive organization (Hultsch, 1974) might be further predictors of task-specific learning of older adults. Also note, that the effect of processing speed on learning rate turned out to be negative after adjusting for effects of education and dropout on task-specific learning. We conducted an additional analysis that included only processing speed, working memory, and age as predictors of task-specific PA learning without education and dropout as further predictors. Within this model processing speed had an effect of .21 on learning rate. Thus, the reverse (negative) effect of processing speed on learning rate in the final model might be due to the inclusion of education and dropout as predictors of learning, not due to the inclusion of age as a predictor.

Thus the positive effect of processing speed on learning rate in the previous unadjusted model changes with the adjusted model.

Regarding effects of education on task-specific learning, one should note that all participants of the present study were relatively high educated. Possibly the internet procedure of the present study resulted in a select sample of older adults who might be higher educated and/or more likely to have experience in using a computer. All participants in the present study possessed a computer, thus, they had some computer experience. Thus our model remains to be further validated with a sample who has less computer experience and for a sample with a broader range of years of education.

Note that the present study investigated task-specific PA learning of older adults in a naturalistic context, in which participants conducted the test battery self-regulated at home, in order to gain insights into optimal conditions of task-specific learning that are related to the natural process of learning. A limitation of this procedure might be that there is no information available regarding what participants actually did during task completion. Compared to a lab-based sample there is less control over correct task completion. In the present study it would be possible that participants were writing the word pairs during study trials. To find indicators of an incorrect task completion, we considered the duration of task performance and also calculated the correlation between this duration and recall performance. Hence, if participants were taking time to write down information we would expect the time on task to be relatively long in the internet sample as it would take more time to write down responses and to look up answers to items as they were presented for recall in a different random order compared with presentation. Furthermore, a correlation between duration of task and recall performance would indicate the possibility that participants did anything in order to succeed in the PA task resulting in actual higher recall performance. Both indicators suggested that participants in the present study completed the PA task without any additional activity that was not part of the instruction of the task. The duration of task completion was relatively short ($M = 4.36$ minutes, $SD = 1.59$) indicating that participants in the current sample did not spend hours trying to get the answers right. Furthermore, the correlation between task duration and recall performance was not statistically significant; individuals who required more time were not more likely to get higher PA scores ($r = .128$, $p = .312$).¹

Unlike typical lab-based research, participants could complete the tasks at a time and place of their choosing. This reduces pressure on participants by allowing them to remain in the comfort of their typical environment and to select a time when they perceive themselves to be prepared and motivated for the testing. In contrast, bringing participants into the lab for this testing may unintentionally induce anxiety, either through the novelty of the lab environment itself or from the implications of performing poorly in front of a research assistant. Additionally, lab-based research is limited to hours of operation that require alteration of the participant's daily routine. Previous work has shown that older adults show better performance on memory tasks that are part of a structured routine (Neupert, Patterson, Davis, & Allaire, 2011; Rose, Rendell, McDaniel, Aberle & Kliegel, 2010). Home-based testing as realized in the present study may reduce performance deficits due to these factors. Mogle (2006) verified that among a computer lab with and without supervisor as well as a location of participants' choosing there were no differences between these conditions regarding factor structures as indicated by measurement invariance. However, it remains an open issue if lab-based assessments would produce different results with regard to task-specific learning trajectories of older adults.

A further open issue of the present study is the question of what the underlying mechanism of task-specific learning might be. In the beginning we argued that in line with Schwenn and Postman (1967) as well as with Wissman et al. (2011) skills required for a PA task are enhanced. However, if a skill and its related mechanisms, as suggested by the growing literature on cognitive skill learning (Rickard, 2007; Touron, Hoyer, & Cerella, 2001; Wilkins & Rawson, 2010), was learned, the exact skill remains an open issue.

In conclusion, the present study emphasized the role of individual differences and cognitive correlates of task-specific PA learning over several days. Future measurement intensive studies should take into account individual differences in task-specific learning and further analyze between-person differences in task-specific learning across the lifespan. Further questions remain as to the generality of such learning effects across stimuli and task type and how particular task-specific PA learning may transfer and affect other types of task-specific learning without a PA component.

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Figure 1.

Predicted trajectories of the Model HypCog by ability groupings. +1/-1 SD WM = Mean trajectory of learning by +1 SD of working memory (upper curve) and by - 1 SD of working memory (lower curve). +1/-1 SD PS = Mean trajectory of learning by +1 SD of processing speed (upper curve) and by - 1 SD of processing speed (lower curve). Average = average learning trajectory of all participants. $N = 65$.

Figure 2. Predicted trajectories of the Model HypCogAge by age groupings. +1/-1 SD Age = Mean trajectory of learning by +1 SD of age (upper curve) and by -1 SD of age (lower curve). Average = average learning trajectory of all participants. $N = 65$.

Table 1
Descriptive Statistics of Age, Years of Education, WM, PS, and seven daily measures of PA

	Mean	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Age	65.34	4.80		-.05	-.14	-.18	-.10	-.23	-.10	-.02	-.37	-.13	-.04
2. YEduc	14.20	3.55			.17	.08	.04	.27	.02	.05	.25	-.17	-.15
3. PA2	8.72	7.34				.70*	.71*	.61*	.57*	.56*	.66*	.31	.11
4. PA3	11.17	9.61					.81*	.79*	.79*	.81*	.81*	.51*	.16
5. PA4	11.77	10.26						.78*	.80*	.82*	.70*	.40*	.08
6. PA5	11.94	9.69							.86*	.86*	.87*	.47*	.19
7. PA6	14.02	10.73								.95*	.87*	.42*	.07
8. PA7	13.51	10.32									.83*	.35	.12
9. PA8	15.20	12.02										.51*	.32
10. WM	5.42	2.40											.37*
11. PS	37.22	1.59											

Note. $N = 65$. YEduc = Years of Education. WM = Working Memory. PS = Processing Speed. PA2-PA8 = Paired Associates Performance of Session 2-8.

* $p < .01$ (two-tailed).

Table 2

Parameter Estimates and Fit Statistics

Parameter	Model				
	Exp	Pow	Hyp	HypCog	HypCogAge
Fixed effects					
α	16.52*	19.53*	16.55*	14.55*	14.91*
β	9.68*	9.39*	7.74*	8.83*	10.44*
γ	0.53*	0.26*	1.04*	1.08*	0.64*
WM on α				2.25*	2.44*
WM on β				1.01*	1.04*
WM on γ				0.10*	0.50*
PS on α				1.27*	2.15*
PS on β				0.89*	0.69*
PS on γ				0.27*	-0.39*
Age on α					-0.33*
Age on β					-0.15*
Age on γ					-0.02
Drop on α					0.28
Drop on β					-0.86*
Drop on γ					0.86
Educ on α					0.60*
Educ on β					0.29
Educ on γ					0.22
Random effects					
Std α	11.11*	15.78*	11.06*	11.47*	9.66*
Std β	6.54*	7.15*	5.51*	5.63*	5.81*
Std γ	0.38*	0.33*	1.28*	0.35*	0.57*
Std res	3.63*	3.88*	3.62*	3.82*	3.41*
Correlations					

Parameter	Model				
	Exp	Pow	Hyp	HypCog	HypCogAge
$\alpha \beta$	.75*	.87*	.76*	.83*	.58*
$\alpha \gamma$	.09*	.18*	.01*	.39*	.04*
$\beta \gamma$	-.04	.07	-.01*	.04	.00
Goodness of fit					
-2 LL	2106.4	2114.4	2093.7	2095.1	2061.3
AIC	2126.4	2134.4	2113.7	2127.1	2111.3
BIC	2148.1	2156.1	2135.4	2161.9	2176.9

Note. $N = 65$. Fit-Indices of the linear Model: -2 LL = 2136.1, AIC = 2148.1, BIC = 2161.2; Fit-Indices of the quadratic Model: -2 LL = 2117.9, AIC = 2137.9, BIC = 2159.7. α = asymptotic performance; β = initial level; γ = learning rate. WM = working memory; PS = processing speed; age = grand-mean centered; Drop = dropout with 0 = no missing, 1 = missing; Educ = years of education; exp = exponential function; pow = power function; hyp = hyperbolic function; HypCog: learning modeled by a hyperbolic function, working memory and processing speed as predictors of learning; HypCogAge: learning modeled by a hyperbolic function, working memory, processing speed, dropout, education, and age as predictors of learning.

* $p < .05$ (one-tailed).