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ScienceDirect
Learning and Individual Differences 17 (2007) 231–240
Learning and Individual Differences
www.elsevier.com/locate/lindif

Correlates of individual, and age-related, differences in short-term learning ☆

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Received 19 May 2006; received in revised form 5 December 2006; accepted 27 January 2007

Abstract

Latent growth models were applied to data on multitrial verbal and spatial learning tasks from two independent studies. Although significant individual differences in both initial level of performance and subsequent learning were found in both tasks, age differences were found only in mean initial level, and not in mean learning. In neither task was fluid or crystallized intelligence associated with learning. Although there were moderate correlations among the level parameters across the verbal and spatial tasks, the learning parameters were not significantly correlated with one another across task modalities. These results are inconsistent with the existence of a general (e.g., material-independent) learning ability.

Keywords: Verbal learning; Spatial learning; General learning ability; Intelligence; Growth curve models

Understanding individual differences in learning has been a major focus for research, and has concerned both psychologists and educationists for many years (e.g., Ackerman, Kyllonen, & Roberts, 1999; Ackerman, Sternberg, & Glaser, 1989; Gagné, 1967; Jonassen & Grabowski, 1993; Sternberg, 1984). Learning is commonly defined as the difference between initial and final levels of performance on a cognitive task (Glaser, 1967; McGeoch, 1942; Woodrow, 1946). Individual differences in learning have been found in a wide range of cognitive tasks, including verbal learning (Jenkins, 1967), motor learning (Fleishman, 1967), problem solving (Anderson, 1967), and so on. There have also been many attempts to investigate relationships between learning and intelligence (Ackerman et al., 1989; Duncanson, 1964; Gagné, 1967; Glaser, 1972, 1976; Jonassen & Grabowski, 1993; Stake, 1961; Woodrow, 1946). Correlations between learning and intelligence have generally been positive, but often not statistically significant. Similar to the study of general intelligence (e.g., Cattel, 1971; Herrnstein & Murray, 1994), there have been attempts to investigate general learning ability (e.g., Duncanson, 1964; Horn, 1989; Matzel et al., 2003; Snow, Kyllonen, & Marshalek, 1984; Stake, 1961; Woodrow, 1946). Factor analyses of intercorrelations among measure of

☆ Timothy Salthouse was supported by grants R01 AG 019627 and R37 AG 024270 from the National Institute on Aging; and Elliot Tucker-Drob was supported by grant T32 AG 020500 from the National Institute on Aging.
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1041-6080/$ - see front matter
doi:10.1016/j.lindif.2007.01.004

learning from different tasks have revealed that no general learning ability existed, and rather that learning was specific to a particular type of task (e.g., Duncanson, 1964; Snow et al., 1984; Stake, 1961).

Although results from previous studies have generally been consistent, there is still controversy concerning the relation between intelligence and learning and the existence of a general learning ability. Because intelligence is sometimes defined as "the ability to learn" (Thorndike, 1924), and because Cattel's (1971) investment theory of fluid and crystallized intelligence is based on the hypothesis that learning is the result of the investment of ability, it seems that intelligence and learning should be correlated. Furthermore, recent studies based on new analytic techniques found that learning was related to several measures of intelligence for older adults (e.g., Jones et al., 2005). One of the major critiques of the previous findings is the use of difference scores to measure learning. The major limitations of difference scores include: (1) difference scores ignore performance on intermediate trials and only utilize the information from the first and last trials, (2) difference scores tend to be highly correlated with the initial scores, and (3) difference scores often have low reliability which could attenuate relationships with other variables. These limitations restrict the value of difference scores in research on individual differences (e.g., Cronbach & Snow, 1997; Lohman, 1999; Snow et al., 1984).

Growth curve models have been recommended as an alternative to difference scores for both theoretical and methodological reasons (e.g., Bock, 1991; McArdle & Andeson, 1990; Rogosa, Brandt, & Zimowski, 1982). Several recent studies have attempted to model short-term learning in a multiple-trial word recall task using contemporary growth curve modeling techniques (e.g., Jones et al., 2005; Poreh, 2005; Nettelbeck, Rabbitt, Wilson, & Batt, 1996; Royall, Palmer, Chiodo, & Polk, 2003; Royall, Palmer, Chiodo, & Polk, 2005; Warschausky, Kay, Chi, & Donders, 2005). Among the results of these studies were significant relations between the learning parameters in these models and age, race/ethnicity, speed of processing, verbal knowledge, and global cognitive ability level. However, growth curve models have only been applied to one type of learning task, and the examination of relations between learning and intelligence, especially fluid and crystallized intelligences, are still rare. Furthermore, to our knowledge, there is no study investigating the existence of a general learning ability across different types of materials using sophisticated growth curve modeling techniques. Finally, the reliability of learning measure derived from growth curve models also needs to be investigated because measures of learning could not be expected to be correlated if they are not reliable.

The current study aims to address these issues with growth curve analyses of two data sets. First, we examine correlations among the growth curve parameters for tasks involving verbal and spatial information to determine the plausibility of a general (i.e., material-independent) learning ability. Second, we examine relations between measures of fluid and crystallized abilities and the growth curve parameters to determine whether, as often hypothesized, higher levels of intelligence are associated with faster learning. Third, we examine correlations of the growth curve parameters derived from parallel forms of a verbal learning task on three separate sessions to estimate the reliability of the parameters. Finally, we examine whether the above described relations varied across different age groups.

1. Growth curve models

Fig. 1 depicts a path diagram for the basic growth curve model used in the analyses. The observed variables are drawn as squares, unobserved or latent variables are drawn as circles, and constants are represented by the triangle. The squares labeled y1 through y5 are the observed scores on trials 1 through 5, respectively. L in the circle is the initial level of performance, and μ_{L} is mean of the initial level across all the participants. σ^2_{L} is the variability around the initial level which represents the inter-individual differences. S in the circle corresponds to the slope, and μ_{S} is mean of the slope across all the participants. σ^2_{S} represents the variability, or individual differences, around the slope, and σ_{LS} on the double headed line represents the covariance between initial level and slope. The circles labeled e1 through e5 are random errors, and their variances (σ^2_{e}) are assumed to be equal. L and S are random-effects parameters which are different for each individual, whereas μ_{L} and μ_{S} are fixed-effects parameters which are the same for all the participants.

The model indicates that the observed variables y1–y5 can be viewed as determined by the initial level (L), the slope (S), and the error (e). Different shapes of the growth curve can be produced by adjusting the weights of α_1 through α_5. For example, assigning them the values 1 through 5 would result in a linear growth curve. In our analyses the value of α_1 was fixed to 0, the value of α_5 was fixed to 1, and the values of α_2, α_3, and α_4 were estimated. This particular model, in which the weights or basis coefficients determine the shape of the growth curve, is known as a latent growth model, and it has the advantage that the form of the function is determined by the data rather than specified a priori. The S parameter in this model can be interpreted as the estimate of learning.