On the relationship between the retrieval of information and learning: the influence of deep processing

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Abstract

This study investigates the relationship between learning and the retrieval of information. In particular, the influence of deep learning in contrast to shallow learning on this relationship is considered. A sample of 183 university students completed a retrieval task (Posner's Task) as well as tasks tapping associative and complex learning. All tasks were designed to include several treatment levels that enable the separation of the effects of retrieval and learning processes respectively from the effects of auxiliary processes, as for example, perceptual and motor processes that are necessary for completing a task. Results showed that there were substantial relationships between retrieval and complex learning ($r = .56$) and also associative learning ($r = .34$). The relationship due to complex learning showing characteristics of deep learning proved to be substantially larger than the relationship attributed to shallow learning.

Key words: retrieval, associative learning, complex learning, deep processing, Posner's Task

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This paper focuses on the relationship between the retrieval and the storage of information in the knowledge base through two types of learning. Since the retrieval of information seems to reverse the processes employed in the storage of information, expecting a close relationship between the two seems to be reasonable. Furthermore, the observation that both learning and retrieval processes contribute to intelligence also suggests that there may be common ground (Kaufman, DeYoung, Gray, Brown, & Mackintosh, 2009; Liesefeld, Hoffmann, & Wentura, 2016; "Wang, Ren, & Schweizer, 2016; Williams & Pearlberg, 2006). However, it is not the learning and retrieval of the same piece of information that is in the focus of this study. Instead it is the efficiency of retrieval and use of information stored a long time ago and its relationship to the ability of storing information in general that is of interest. This general case differs from the specific and immediate one in that it implies the possibility of modifications of the knowledge base containing the stored information. It is conceiveable that the integration of new information into the knowledge base impairs the access to older information or that unconscious background processes may bring about a reorganization of the internal structure of the knowledge base (Dudai, 2004) that makes it difficult to access the older information. In the long run these modifications may lead to the gradual disappearance of an originally close relationship. The current study therefore aims to shed light on the question of how learning relates to the retrieval of information.

On the efficiency of retrieving information

Retrieving information stored in the knowledge base is one of the most important elements of higher mental processing (Mogle, Lovett, Stawski, & Sliwinski, 2008; Unsworth & Engle, 2007; Unsworth, 2010). Items of information originating from various external sources and from the knowledge base are related to each other in pursuing a variety of complex goals. Most higher-mental processing is complex in that it requires the use of information stored in the knowledge base as either input for processing or as a tool for transforming other information. For example, retrieved information such as previous experiences or knowledge of general rules provides the basis for addressing problems in intelligence tests (Mogle et al., 2008; Unsworth, 2010).

One cognitive test that has established itself as a standard measure of the efficiency in retrieving information is Posner's Task (e.g., Altmeyer, Schweizer, Reiss, Ren, & Schreiner, 2013; Posner, Boies, Eichelman, & Taylor, 1969; Posner & Mitchell, 1967). This task requires a participant to compare two stimuli stored in the knowledge base. Such a comparison has to occur on one of three different levels of processing. Generally, simple stimuli such as letters or digits are used in this Task. Therefore, the demands during testing are quite low, and errors are usually rare so that processing speed is frequently employed as performance measure. Posner's Task was included in many studies that investigated the speed-ability relationship (e.g., Altmeyer, Schreiner, & Schweizer, 2009; Sheppard & Vernon, 2008).

The first level of processing of Posner's Task (i.e., physical identity level) focuses on the physical features of the stimuli and does not require the retrieval of information from the knowledge base. In the second level the comparison focuses on the primary meaning of

the stimuli (i.e., name identity level) so that information regarding the primary meaning needs to be retrieved. The third level requires the comparison of the stimuli with respect to a specific property (i.e., categorical identity level); it is considered as secondary meaning that means deep search in the knowledge base compared to the second level. A recent investigation of the structure of data collected by means of this task confirms that the three levels reflect different ways of cognitive processing (Schweizer, Altmeyer, Rammsayer, & Troche, 2016).

On the storage of information via learning

As already indicated, the successful retrieval of information depends on how it is stored into the knowledge base. Therefore, this section discusses the aspects of the storage of information that are pivotal for the research work reported in the empirical sections of this paper. According to Hunt's library-metaphor (1978), like a library that hosts a large amount of books, the knowledge base comprises many items of information. In both cases the fast access to the item of interest, may it be a specific book or a specific piece of information, depends on an efficient storing system that includes additional information concerning the location of specific contents.

This analogy illustrates that storing information in the knowledge base requires not only the transfer of information, but also the appropriate allocation of information within this base. Active integration is necessary in order to arrive at the most appropriate allocation; it means "deep learning" as opposed to "shallow learning" (Struyven, Dochy, Janssens, & Gielen, 2006). Deep learning requires a person to actively comprehend new information, analyse it and allocate it close to related items of information (Bereiter & Scardamalia, 1989). The newly stored information is allocated well if it shows links to virtually all other items of information representing related contents. This kind of intensive integration of new information into the knowledge base referred to as knowledge elaboration (Kalyuga, 2009) is normally achieved in a time-consuming process. It characterizes complex learning that includes the construction of a mental representation as an intermediate step in the transfer of information to the knowledge base.

A similar line of thought characterizes Craik and Lockhart's (1972) levels-of-processing model. It also highlights the relationship of the accessibility of information stored in the knowledge base and the depth of mental processing while storing information. "Deep" mental processing is assumed to result in more elaborate and longer lasting memory traces than "shallow" processing (Rose & Craik, 2012; Rose, Myerson, Roediger III, & Hale, 2010). The evidence supporting this assumption is based on a task asking participants to process words based on their visual, phonological, or semantic characteristics. The results suggest that semantic processing during learning yields a better long-term retention than processing that focuses on visual and phonological aspects of the words (Rose et al., 2010). Furthermore, it needs to be added that there is also evidence suggesting that additional imagery improves performance based on semantic processing (Oliver, Bays, & Zabrucky, 2016). It has to be mentioned, that there is also evidence in the literature saying that the additional material poses some additional workload and might distract the learner (Mayer, 2014). However, in this approach it is argued that the identifica-

tion and elaboration of semantic contents that characterize deep processing create links for embedding new information into an already available knowledge base. As a consequence, information subjected to deep processing is accessible and retrievable in many different ways, whereas only a few connections are available for accessing information stored via shallow processing.

Associative and complex learning

The aforementioned two approaches that describe the storage of information in the knowledge base can be linked to two specific types of learning: associative and complex learning. The distinction of associative and complex is in line with the distinction between simple and complex learning which characterizes different types of basic information processing and has been highlighted in past research on information processing (e.g., Schweizer, 1998; Stankov, 2000). A main characteristic of the distinction between the two is the degree of complexity, which is also a main issue in the storage of information in knowledge base (Sweller, 2003, 2005). The lowest degree of complexity in learning is the establishment of an association between two knowledge units.

The term complex learning has been referred to as the integration of knowledge, the acquisition skills and attitudes, and the demands for the coordination of skills in the transfer of what has been learnt from new situations (Kirschner & van Merriënboer, 2008). A major characteristic of complex learning is the special preparation of information for the transfer to the knowledge base that requires contributions of working memory (Ren et al., 2014). It can be compared to the early steps of the model of skill acquisition by Anderson et al. (1997). Although this model reflects the computer metaphor of mental information processing, it also suggests that the processing of complex information implies additional elaborations on the essentials of the contents. This type of learning is likely to lead to an especially elaborate representation and the establishment of robust links between different pieces of information.

In contrast, associative learning is usually defined as the establishment of a new association between at least two items of information. This means the straightforward transfer of information to the knowledge base without further elaboration (Kaufman et al., 2009; Tamez, Myerson, & Hale, 2012; Williams & Pearlberg, 2006). As a result of this way of establishing information, there is a new item of information that is linked to a few other items of information. However, this does not include an elaboration process when integrating the new information into the knowledge base. Instead the strength of the link to some degree seems to depend on instances of attentive retrieval (Dudukovic, DuBrow, & Wagner, 2009). In sum, complex learning shows some similarity with deep processing whereas associative learning does not.

On the purification of latent representations by modeling

This section describes and justifies the modeling approach selected for the research work in order to achieve an especially purified representation of the concepts of interest: cog-

nitive measures usually stimulate auxiliary processes besides the cognitive processes of interest. For example, a reaction time task for measuring speed in list searching is not only determined by the intake and analysis of information but also by a motor response. This means that the motor response contributes to processing time. This additional process is no problem in an experiment that compares the processing times observed in completing, for example, three- and six-item lists because in each case there is the same contribution to processing time. In contrast, if correlations are computed and investigated, the additional contribution matters. It can lead to an increase or a decrease of the correlation with another score because of this additional contribution that means systematic error; alternatively it is addressed as impurity in measurement (Miyake, et al., 2000; Schweizer, 2007; Van Zomeren and Brouwer (1994).

The combination of experimental manipulation and fixed-links modeling of the experimental effect enables purification in the sense of the separation of systematic error from the contributions of cognitive processes of interest (Schweizer, 2006, 2008). This approach requires that the assumptions regarding the processes of interest and the auxiliary processes are transformed into constraints that replace the factor loadings. In confirmatory factor analysis theses constraints are associated with different latent variables and cause the decomposition of the true variance into variance due to the processes of interest and due to auxiliary processes. As a consequence of the decomposition, a purified latent variable is available that can, for example, be used for the investigation of construct validity.

The current study

The main objective of the current study is to investigate the relationship between the storage and retrieval of information. Since the research interest is on the general properties of the storage and retrieval of information, the contents to be stored and retrieved may differ from each other and even a temporal distance may separate the storage and retrieval of the considered information. Because of the assumed long-term dynamics regarding the structure of the knowledge base a small to medium relationship is expected. Furthermore, dependency on the type of learning is hypothesized to characterize the relationship. A stronger relationship with retrieval is expected for complex learning than for associative learning since the two types of learning are characterized by different degrees of elaboration when information is transferred into the knowledge base.

Method

Participants

The sample comprised 183 university students (62 males) aged between 18 and 45 years of age (mean age = 23.90; SD = 4.96). They were either paid or received course credit for participating.

Experimental tasks

Since all participants were either of German nationality or spoke German fluently, all test materials and instructions were in German.

Posner's Task. Posner's Task (Posner & Mitchell, 1967) was used to capture the efficiency of retrieval of information from the knowledge base. We employed the original version of the task that includes three treatment levels. In the first treatment level (physical identity) participants were asked to judge whether two letters were physically the same (e.g., 'A A'), whereas the second treatment level (name identity) demanded a decision on whether the two letters were semantically the same (e.g. 'A a'). In the third treatment level (categorical identity) the participants had to decide whether the letters possessed categorical equality (either vowels or consonants). The letters were presented on the computer screen and participants were asked to respond as quickly and accurately as possible. Response time was automatically recorded for each trial.

After completing 10 practice trials, each participant completed 60 trials, evenly distributed over the three treatment levels by being arranged in six blocks (two for each level) of ten trials each. The order of the blocks was: Level 1, Level 2, Level 3, Level 1, Level 2, Level 3. This order was meant to minimize possible position effects while avoiding too many changes between different levels. After each block the participant was informed that a new block was next, which level it belonged to and what the requirements were. The participants were then able to start the next block by clicking a button whenever they were ready. The average response time was computed for each treatment level by averaging the measurements of the correctly answered trials. Incorrectly answered trials were omitted because a false response may be due to incorrect cognitive processing, which would make a correct estimation of the response time impossible. There were about 2% of incorrectly answered trials.

Complex learning task. This task was employed to assess complex learning as the acquisition of rules from examples (Schweizer & Koch, 2002). The stimuli consisted of 32 arrays of symbols. Each array included multiple "o" and "+" symbols that were composed to follow one of five rules. The 32 arrays were grouped into five sets each associated with a particular rule. Two sets implied the application of a simple rule (sets G and H), and included four arrays each consisting of three symbols. They were considered as the first treatment level.

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O   O   O
O   +   +
+   O   O
+   +   +
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Figure 1:
Example from the complex learning task for a set representing a simple rule

The participants were informed that the rule always defined the "relationship" between the last symbol of the array and the other symbols. The arrays of the example in Figure 1 follow the rule that the last symbol of an array is always identical with the second to last symbol. The other three sets that constituted the second treatment level followed the same principle but represented more complex rules (sets J, K and L). Each set included eight arrays of four symbols.

A detailed on-screen instruction informed participants that there would be a test afterwards and that this test would require them to reproduce the last symbol of each array when presented with the other symbols. They were also informed that the identification of the rule would facilitate learning considerably. The learning of each set was started by pressing the key of a letter marking a specific rule (G, H, J, K, and L), and one of the arrays associated with the rule appeared on the screen. There was only one array presented on the screen at one time so that direct comparisons among different arrays associated with one rule were prevented. Participants could go up and down for inspecting the different arrays within a set by pressing the "up" or "down" keys. This way they could find information for developing hypotheses and checking hypotheses by proceeding to other arrays within a block. They were not allowed to take notes.

Participants had 10 min to inspect the arrays characterizing the rules on the screen of a personal computer and to memorize them. In the testing phase the participants had to process an answer sheet. There were five blocks, each including four arrays of symbols and rules (G, H, J, K, and L) assigned to these blocks. The arrays used were not part of the training material. In each case the last symbol of an array was missing, and the participants were asked to determine what the last symbol should be according to this rule. No time limit was imposed on the responses. Responses to each array were recorded as binary data. Besides a total score, a score was computed for each one of the five blocks.

Associative learning task. This task aimed at the assessment of the simple transfer of information to the knowledge base (Schweizer & Koch, 2002). Unlike in the complex learning task it was not necessary to analyze the information and to derive rules before transferring the outcome. This task consisted of a list of 20 names and definitions of what they mean. The names were made up and did not exist in the German language. They did however include familiar German syllables. Each name consisted of six or seven letters. The definition identified the names as something merging two existing concepts. For example, the word ORKINOL stood for a combination of salad oil and liqueur.

The task started with the learning phase, in which the participants were presented with the 20 names and their definitions on a computer screen. The names were presented individually together with the corresponding definitions, and the participants could skip from one name to the next one by using the "up" and "down" arrows. They had five minutes to memorize as many of the name-definition combinations as possible. Five minutes after the learning phase, participants were presented with a piece of paper with the same 20 names and definitions. In some cases, however, the definitions were switched between names. This provision resulted in some names being paired with their original and correct definitions, while other names were now linked to incorrect definitions. None of the names or definitions was used twice so that there were no special relationships among any items. The

correct and incorrect combinations were arranged randomly. Participants were asked to decide for each pair, whether the name was matched with its correct definition or not. The responses were recorded as binary data. A total score of correct answers was computed and used for data description. Four subscores were additionally computed by splitting the items into 4 blocks (Items 1-5, 6-10, 11-15, 16-20) in order to reduce the otherwise large number of indicators in confirmatory factor analysis. Only these subscores obtained for the blocks were used as part of the confirmatory factor model.

Statistical analysis

Structural equation models were constructed to investigate the relationship between the speed of retrieval of information and the performance in reproducing the stored information. The construction of the models was theory-driven. In some cases the characteristics of the data required an additional adaptation. These models were complex models combining two different models of measurement; one of them was even a twofold model.

The model of measurement associated with Posner's Task was an extended version of the fixed-links factor model (Schweizer, 2006a, 2006b, 2008) proposed for Posner's Task taken from another study (Altmeyer et al., 2013). There were three manifest variables associated with the three treatment levels and two latent variables reflecting the core cognitive processes (i.e., retrieval processes) and auxiliary processes (e.g., motor processes). Following Altmeyer et al. (2013) the loadings on the latent variable reflecting auxiliary processes were constrained to 1 while the loadings on the latent variable representing core processes to 0, 1 and 4 for the levels 1, 2, and 3 in corresponding order.

Since the expectations regarding complex and associative learning were less clear than the ones regarding Posner's Task, an extended bifactor model (Canivez, 2016) served as the twofold model of measurement for representing complex and associative learning. The bifactor model enables to have double factor loadings of manifest variables on latent variables without constraining these factor loadings. It was a twofold model of measurement for the two learning tasks since each of them included several different treatment levels that could provide the basis for distinguishing between core and auxiliary processes. This model of measurement included three latent variables and nine manifest variables. One of them represented the auxiliary processes of learning (e.g., perceptual and motor processes that are necessary for completing the task but are not genuine learning) and the other two reflected the core processes of complex learning and of associative learning respectively. All manifest variables of the two learning tasks loaded on the latent variable denoted as "Associative / complex learning auxiliary processes". Three of the five manifest variables associated with more complex rules (i.e. J, K, and L) had additional loadings on the latent variable denoted as "Complex learning core processes". Also the four manifest variables of the associative learning task loaded on the latent variable denoted as "Associative learning core processes".

In a next step the learning-based latent variables were related to the retrieval-based latent variables. In the first and second models the core processes of complex learning and associative learning were separately linked to the core processes of retrieval in order to

examine the relationship of the two types of learning and retrieval. At the same time the two latent variables representing auxiliary processes were related to each other. Then, the third model, which included links between both latent variables of complex learning and associative learning and the latent variable of retrieval was tested.

The data were analyzed by means of LISREL (Jöreskog & Sörbom, 2006) using the maximum likelihood estimation method with the covariance matrix as input. In order to avoid artifactual results due to the investigation of dichotomous items (Kubinger, 2003), covariances of scores obtained as counts of correct responses were computed. The following set of fit statistics and evaluation criteria given in parentheses were considered (see Distefano, 2016; Kline, 2005): normed χ^2 ($=\chi^2$/df) ($\leq$2 indicating good model-data fit), RMSEA ($\leq$.06 indicating good model-data fit), SRMR ($\leq$.08 indicating good model-data fit), CFI ($\geq$.95 indicating good model-data fit), and TLI ($\geq$.95 indicating good model-data fit). Since positive correlation coefficients were expected for the latent variables representing efficiency in learning and efficiency in retrieval, the tests of the correlation coefficients were one-sided.

Results

Descriptive results

The mean reaction times (in milliseconds) and the corresponding standard deviations for Posner's Task were 740 ms (SD=210 ms), 790 ms (SD=190 ms) and 1210 ms (SD=390 ms) for the three treatment levels in corresponding order as illustrated in Figure 1.
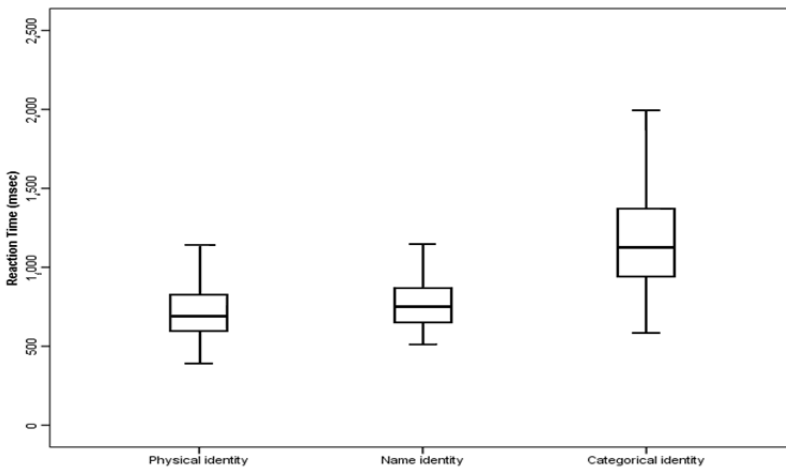

Figure2:
Mean reaction times observed for the physical, name and categorical identity conditions of Posner's Task

The mean scores observed for the subscores of the Associative Learning Task were 4.16 (SD=.97), 3.68 (SD=1.30); 3.63 (SD=1.21) and 3.99 (SD=1.03) respectively, with a maximum possible score of 5 for each subscore. The mean scores observed in the Complex Learning Task were 3.33 (SD=.87), 3.06 (SD=1.15), 2.61 (SD=1.12), 2.23 (SD=1.24) and 2.38 (SD=1.36) for the five treatment levels in corresponding order.

Results observed in structural equation modeling

As suggested by Anderson and Gerbing (1988) the models of measurement for each task as well as the models representing the relationships between the tasks were investigated separately.

The model of measurement representing retrieval showed the following fit results: χ^2 (1) =2.87, normed χ^2 =2.87, RMSEA = .10, SRMR = .06, CFI=.99, TLI=.95. Most of the fit statistics were above or beneath the corresponding cut-offs indicating a good model fit. Two indices normed χ^2 and RMSEA only showed an acceptable fit. The fit results for the model of measurement representing the learning tasks were as follows: χ^2 (20) = 19.22, normed χ^2 =0.96, RMSEA = .00, SRMR = .00, CFI=1.00, TLI=.95. All the fit statistics were well above or beneath the corresponding cut-offs, indicating a good model fit.

The model considering the relationship between associative learning and retrieval yielded the following fit results: χ^2 (49) = 63.62, normed χ^2 = 1.29, RMSEA = .04, SRMR = .07, CFI = .97, TLI = .95. A good model fit was indicated. The link relating associative learning to retrieval showed a standardized regression weight of .34 (t = 1.96, p < .05). It indicated that associative learning and retrieval shared 11.6 % of common variance.

The model considering the relationship between complex learning and retrieval yielded the following fit results: χ^2 (49) = 58.91, normed χ^2 = 1.20, RMSEA = .03, SRMR = .07, CFI = .97, TLI = .97. All the fit statistics were well above or beneath the corresponding cut-off, indicating a good model-data fit. The link observed between complex learning core processes and retrieval showed a standardized regression weight of .57 (t = 2.65, p < .05). It indicated that complex learning and retrieval shared 32.5 % of common variance.

The complete model with relationships of the three learning latent variables on one hand and two retrieval latent variables on the other hand yielded the following fit results: χ^2 (47) = 53.12, normed χ^2 = 1.13, RMSEA = .03, SRMR = .06, CFI = .98, TLI = .97. Again the model showed a good fit according to the criteria. The standardized parameter estimates, numbers used for fixations and the standardized error component for the measurement model parts of the complete model are presented in Table 1.

An illustration of the complete model with standardized parameter estimates is included in Figure 2.

This Figure includes numbers without parentheses and numbers given in parentheses. The numbers without parentheses were estimated jointly whereas the numbers given in parentheses were estimated separately. The first correlations suggested between 28 and 33 percent common variance while the second ones between 7 and 12 percent only. The differences of the numbers indicated that there was some overlap of the correlations with

retrieval. All the correlations among core processes proved to be substantial. Furthermore, three out of the four substantial correlations reached the level of significance not only in the one-sided test but also in the two-sided test. The exception was the correlation of associative learning core processes and retrieval core processes when there was joint estimation. Moreover, the correlation of complex learning core processes and retrieval core processes was larger than the correlation of associative learning core processes and retrieval core processes. The z-difference of the two correlations was $z = 16.93$ ($p < .01$).

Table 1:
Standardized Parameter Estimates, Fixations (fixed links) and Standardized Error Component (Error)

Indicator	Associative learning core processes	Complex learning core processes	Associative / complex learning auxiliary processes	Retrieval auxiliary processes (fixed links)	Retrieval core processes (fixed links)	Error
Associative learning 1	0.62		0.15			0.58
Associative learning 2	0.81		0.11			0.60
Associative learning 3	0.77		0.16			0.59
Associative learning 4	0.67		0.06			0.58
Complex learning 1			0.64			0.51
Complex learning 2			0.65			0.69
Complex learning 3		0.36	0.50			0.71
Complex learning 4		0.67	0.25			0.68
Complex learning 5		0.34	0.31			0.89
Posner task 1				1	0	0.29
Posner task 2				1	1	0.15
Posner task 3				1	4	0.54

Note. The numbers are parameter estimates with the exception of those identified as fixations (please see columns characterized as *fixed links*).
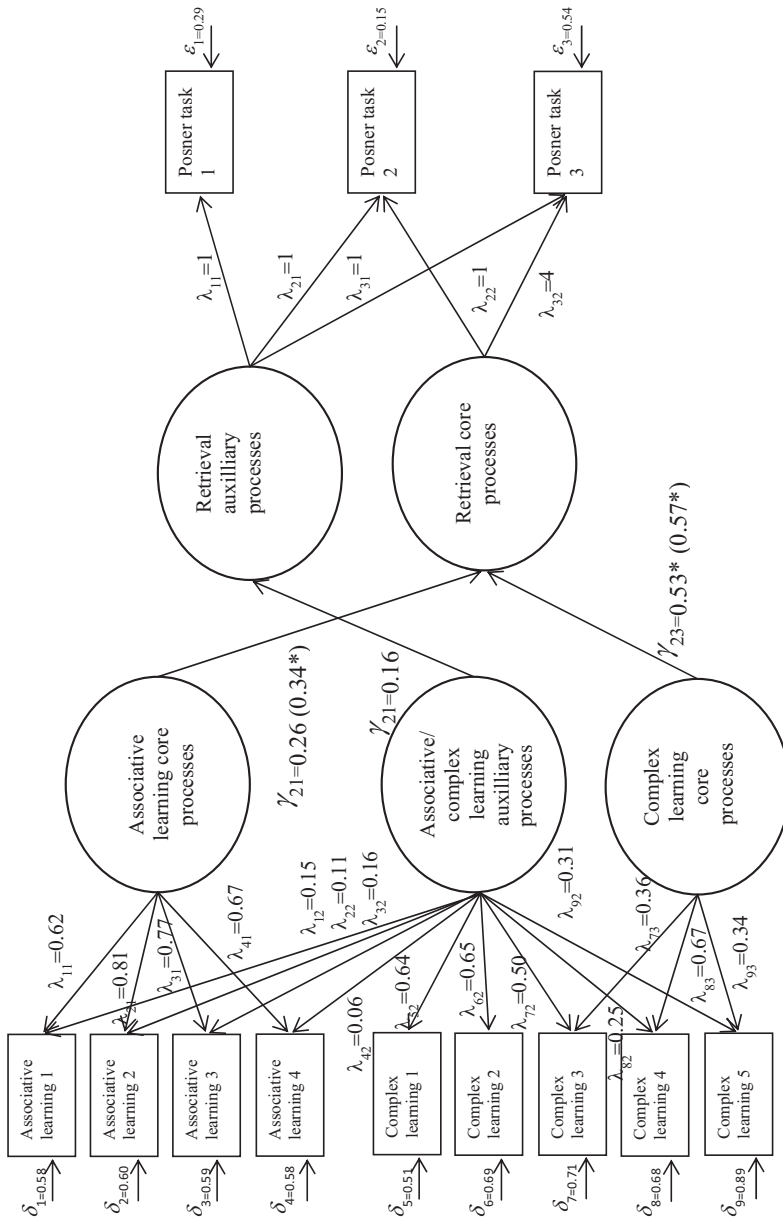
Figure 3:

Optimized full structural model using the fixed-links approach with completely standardized parameter estimates and standardized error components. The numbers in parenthesis were estimated separately

Discussion

At first view and without a clear idea of the dynamics inherent in the knowledge base, one may expect an almost perfect relationship between the storage and retrieval of information. It may appear as if the retrieval of information is nothing but the reversal of what happens when storing new information in the knowledge base. However, research focusing on the malleability of memory suggests something different (Loftus, 2003). The contents of the knowledge base appear to be exposed to various influences and are likely to undergo some changes in the long run. Therefore, we postulated the observation of a small to medium rather than a large correlation between learning and retrieval of information. The outcomes of the empirical investigation are in line with this postulation. No one of the correlations between learning and retrieval reaches a size suggesting that more than 50 percent of the observed variance is common variance.

The small size of the correlation between associative learning and retrieval is likely to be due to the type of learning new information. Associative learning is achieved by creating a rather superficial representation of the new information in the knowledge base. It amounts to the establishment of a new knowledge item in tying it to a very few already available items only. It means a minor modification of the knowledge base. The new knowledge item does probably not reflect major characteristics of the general structure and unique properties of the knowledge base. As a consequence, the success in retrieving these items in probe trials may depend to a larger degree on random processes, as they are described by diffusion models (Ratcliff, 2002), than on the structure and properties of the knowledge base.

In contrast, performance in retrieving information according to Posner's Task can be assumed to reflect general characteristics of the knowledge base. The to-be-retrieved information can be assumed to be easily accessible by well-established pathways. These pathways can be perceived as the result of a kind of compilation, as is suggested by the model of skill acquisition (Anderson et al., 1997) in using an analogy to making computer programs especially efficient. As a consequence, deviations due to random processes in the search for this information are suppressed. Knowledge elaboration provides the other opportunity to arrange for the good accessibility of the stored information. Due to the large number of established links to already available information, it can be assumed that accessibility reflects the structure and properties of the knowledge base. Therefore, the larger correlation for complex learning is not really a surprise.

Furthermore, there is the difference between the correlations with associative and complex learning that needs to be addressed. The correlation with complex learning is considerably larger than the correlation with associative learning. This difference is in line with the expectations based on the distinction of deep and shallow learning (Struyven et al., 2006). Complex learning requires participants to consider various aspects of the stimuli and to search the knowledge base when looking for the rule that underlies a set of arrays composed of circles and plus signs. A possible side-effect or bonus of this search is the establishment of additional links between new and old information. It also means that more information is transferred to the knowledge base than otherwise and that eventually even a redundant representation is created. As a consequence, there is a compre-

hensive representation of information due to complex learning as compared to a poor representation created by associative learning. This representation is likely to reflect the structure and properties of the knowledge base and, therefore, to show the larger correlation with retrieval.

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