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# Unity or Fractionality of Implicit Learning: A Methodological Aspect

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## Abstract

Although the field of non-conscious learning is full with debating studies about the dissociation of explicit and implicit systems, not much emphasis is laid on the understanding of the applied methods. In the literature we found convertible application of the tests measuring implicit learning without much empirical support. In this study we made a cross-validation examination of the three main tests of implicit learning. The findings supported the ominous demands and showed no correlation among the most frequently used measuring paradigms. These inconsistencies led us to propose an explanation of this behavior of the tests and to outline some further steps in research.

## Introduction

It is almost four decades now since systematic research has set in motion about the phenomenon of implicit learning in cognitive psychology. According to the most common definition of implicit learning, learning is implicit when we acquire new information without intending to do so (Cleeremans, Destrebecqz & Boyer, 1998) and this encoded knowledge can affect our decisions and behavior. In practice we use implicit learning equivalently to what we measure by it's classical tasks.

The best established means of measuring implicit learning include serial reaction time (SRT; Nissen & Bullemer, 1987), artificial grammar learning (Reber, 1969, 1989), covariation learning (Lewicki, Czyzewska & Hoffman, 1987), probabilistic classification learning (Knowlton, Squire & Gluck, 1994) and dynamic systems task (Berry & Broadbent, 1984). So far the literature of implicit learning regarded these methods almost unanimously as comparable measurements of the same phenomenon; however, they have been developed to reveal the dissociation of learning in studies from different backgrounds and via quite dissimilar dependent measures. Apart from our present study there have already been a few ominous demands to direct more attention to the question of equability (Keane et al, 1991; Seger, 1994; 1997; Stadler & Roediger, 1998), but these had little impact.

Seger argues that by the serial reaction time tasks we in fact measure two independent forms of sequential implicit learning (1997). One is learning that is linked to making judgments about stimuli, and the other one is learning that is

linked to motor processing. In the case of dynamic systems experiments she found a third kind of measure, which she called prediction and control. Identifying these three different dependent measures, Seger raises the question of whether these tasks tap related forms of learning with shared knowledge representations, or whether they tap different learning mechanisms with separate knowledge representations.

Other theorists dispute that learning of probabilistic sequences may be implicit, whereas learning deterministic sequences is to some extent explicit (Remillard, 2003). This way the simultaneous implicit and explicit learning can also bias the equability of the measurements taken by different tests.

Stadler and Roediger shed light on an even more confusing property of these implicit learning measuring methods. They analyze them according to their nature of encoding and retrieval. In accord with our present thoughts they describe artificial grammar learning paradigm as a case of implicit encoding and explicit (intentional) retrieval, while in the procedure of serial reaction time task both encoding and retrieval occur under implicit instructions (Stadler & Roediger, 1998). This alterity is crucial enough concerning the supposed dissociation between these two forms of cognition.

Considering the above-mentioned doubts about the validity of these frequently used tests, we made a purposeful examination on the issue. The findings supported these ominous demands and showed no correlation among the three most frequently used measuring paradigms of implicit learning. These inconsistencies led us to propose an explanation of this behavior of the tests and to outline some further necessary steps in research for the field of implicit learning methodology to become clarified.

## Paradigms for Implicit Learning

This study works with cross validation procedure on the three main implicit learning tests. Artificial grammar learning, serial reaction time task, and probabilistic classification learning are all computer-assisted procedures.

**AGL – Artificial Grammar Learning** It was Arthur Reber (1967) who began the systematic study of the phenomenon

with this specifically developed artificial grammar task. In his test he trained the participants by asking them to memorize strings of letters generated from a finite-state grammar. One of the grammars Reber used is shown in Figure 1. This grammar specifies rules, similar to those that exist in natural languages, for ordering string elements. Grammatical strings are generated by entering the diagram at the leftmost node and moving along legal pathways, as indicated by the arrows, collecting letters, until an exit point is reached on the right-hand side. The letter string TSSSXS is grammatical as it can be generated from the diagram, whereas XT'TTVV is ungrammatical, as strings must begin with a T or a P. In AGL studies we use three to eight letter strings.

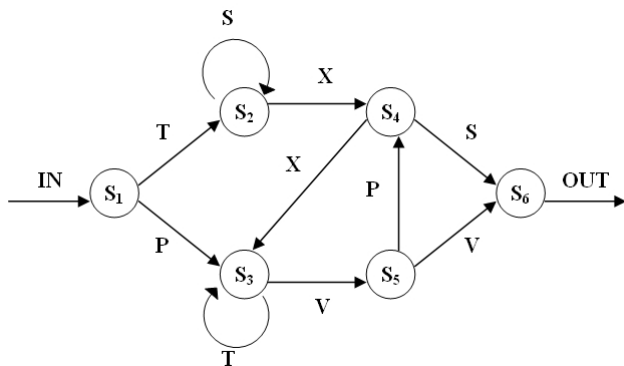


Figure 1: A finite state grammar used by Reber (1989) in his AGL experiments. To produce a grammatical string, one has to move from left to right using the arrows. Each passed arrow adds one letter to the string.

In the first part of the experiment (training phase) the participant has to learn strings of letters. After the appearance of each grammatical string the person has to repeat the correct string. After 50 correctly repeated strings comes the second part, the grammatical prediction phase. In this phase the participants are tested about their knowledge of the hidden rule by informing them of the existence of a set of rules governing the structure of the training items - although they were not told what those rules were - and then asking them to classify novel letter strings as grammatical or ungrammatical. Half of the novel strings are grammatical, the other half are ungrammatical. A metaanalysis of several AGL studies showed, that an average of 60 – 65 % of the participants answers are correct, which is significantly above chance level (Dienes, Broadbent & Berry, 1991). Early studies showed, that while they performed so well on the discrimination task, they could not report on the knowledge that influenced their decisions (Reber, 1967). This kind of dissociation led Reber (1967, 1969) to the conclusion, that people in this kind of situation acquire their knowledge about the rules implicitly.

Although, the results of the study have been repeated several times since (e.g. Servan-Schreiber, 1990), the conclusions were frequently targeted by critics (e.g. Shanks, Johnstone & Kinder, 2002). The usual misgiving is related to the hypothesis, that the knowledge is strictly implicit. Despite

these criticisms, the AGL task still remains one of the mainly used tools in implicit learning studies.

The later developed tasks of implicit learning studies share a feature with artificial grammar learning, that the participant is unaware, or at least partly unaware of the attained knowledge of rules, or patterns. The knowledge usually measured by some performance improvement on the task.

**SRT – Serial Reaction Time** A widely popular type of the implicit paradigms is the sequence learning (SL). In typical SL situations, participants are asked to react to each element of sequentially structured visual sequences of events in the context of a choice reaction task. On each trial, subjects see a stimulus appear at fixed locations on a computer screen and are asked to press the corresponding key as fast and as accurately as possible. Unknown to them, the sequence of successive stimuli follows a repeating pattern, or is governed by a set of rules that describes permissible transitions among successive stimuli, such as finite-state grammars. Subjects exposed to structured material produce shorter reaction times than subjects exposed to random material, thus suggesting that they can better prepare their responses as a result of their knowledge of the pattern. Nevertheless, subjects exposed to structured material often fail to exhibit knowledge of the pattern that they can verbalize. In Nissen and Bullemer's (1987) computerized test the stimuli is a dot on the screen, which can appear above one of four permanently visible unilinear lines, as can be seen in Figure 2.

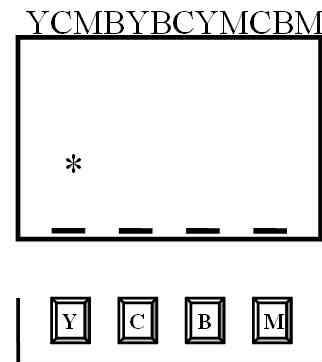


Figure 2: Serial Reaction Time (SRT) presented on computer. The letter string above represents the hidden order of the appearance of the stimulus. The corresponding keys are Y, C, B, and M.

The participants simply have to push as fast as possible the button accompanied with the line, above which the dot appeared. After the successful choice a new dot appears above a different line, and the participants have to push the correct button again. The participants are told that the task is a simple reaction time measuring while unknown to them the appearance of the stimuli is set to a 12 unit long sequence. During the task the given reaction time gradually decreases, yet with the change of the hidden pattern the reaction time radically increases. Interestingly, according to their verbal

report the participants do not realize the pattern, or even the existence of it.

**PCL – Probabilistic Classification Learning** The task developed by Knowlton, Squire and Gluck (1994) is a newer form of measuring implicit learning. The test is made up of a series of predictions. Seeing a set of geometrical symbols, the participants have to predict if the following type of weather will be “rain or sunshine” (see Figure 3). After the appearance of one of the 14 different sets of symbols they have to choose between rain and sunshine. After the decision the correct outcome (rain or sunshine) appears on the screen. The whole experiment consists 50 of these judgments. What the participants do not know is the fixed probabilistic connection between the geometrical sets and the weather outcomes. The probability of the “sunshine” outcome is set to 100%, 86%, 75%, 60%, 50%, 40%, 25%, 14% or 0% identically after each set of geometrical forms. The 50 separate decisions are divided into 10 blocks (Knowlton et al. 1994; Reber, Knowlton & Squire, 1996).

Knowlton et al. studied the question of whether people can acquire the hidden knowledge of the probabilistic rule in this kind of situation. They found, that participants could acquire a significant amount of the knowledge, because there was a significant increase in correct answers between the first and the last block of answers. These findings made this method as a well known tool of implicit learning measurement.

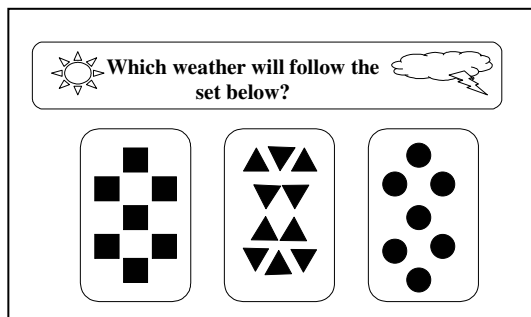


Figure 3: Probabilistic Classification Learning (PCL) presented on computer

As we define the phenomenon of implicit learning by its classical tasks, we have to be extra curious about the question: „What do these tasks really measure?“ The mutual citation of studies using different methods should guide us to the conclusion, that these tasks measure the same hidden ability of people, an implicit learning capacity. In this study we conclude, that this postulation seems to be untenable.

## Experiment

To examine the methodological question, if the three main implicit tasks measure the same hidden variable, we used a cross validation analysis on them. To be able to deduce general conclusions we needed to replicate the classical

procedures, and receive similar implicit learning results. Therefore first we discuss the implicit learning results on the three methods. Our main question however can be summoned as whether the performance on one task can predict the performance on another. In other words whether the comparison of the participants’ implicit learning performance shows correlation among the tasks.

## Method

**Procedure** During the experiment the participants completed the three implicit learning tasks in a row separated by 5 minutes breaks. The experiment lasted 50 minutes. To rule out the effect of fatigue, half of the participants completed the 3 tasks in SRT-AGL-PCL sequence, the other half in PCL-AGL-SRT sequence. Since there was no significant effect of the sequence of tasks, we did not examine the question any further.

The exact versions of the tests were the following:

1. The artificial grammar learning (AGL) procedure used by Reber, Walkenfeld and Hernstadt (1991) as introduced before, showed as MS Power Point© presentation, encoded manually.
2. A computerized version of the revised serial reaction time task (SRT), which was described first by Reber & Squire (1998). In practice, this was the SRT module of the ImpLab© computer program.
3. We also used a computerized version of Reber, Knowlton and Squire’s (1996) earlier introduced probabilistic classification learning task (PCL).

**Participants** The participants were volunteers from an introductory psychology course and first year psychology students at the ELTE University, Budapest, who received small gifts for their participation. The average age of the 40 participants was 22.7 years (S.D.=4.3). They were tested individually.

## Results

The statistical examination of the data verified the conditional assumption, namely we found implicit learning (as defined by the task developers) in all the three tests.

**Artificial Grammar Learning (AGL)** In the rule learning part the participants could give correct answers in 56.5% (S.D. = 6.6) of the decisions. This shows that they acquired some kind of knowledge about the grammar. Though earlier studies found higher percentage of correct answers, the results show similar implicit learning.

**Serial Reaction Time (SRT)** The average reaction time of the 40 participants during the 21 blocks of the experiment can be seen on Figure 4. The diagram shows the significant decrease of reaction times [ $t(39)=7.51, p<0.001$ ] from the first to the twentieth block, which means some kind of learning. The reason of the significant increase [ $t(39)=-10.49, p<.001$ ]

in reaction time between the twentieth and twenty-first blocks is the hidden change of the pattern. These two findings together can lead us to the conclusion, that we tracked the effect of implicit learning.

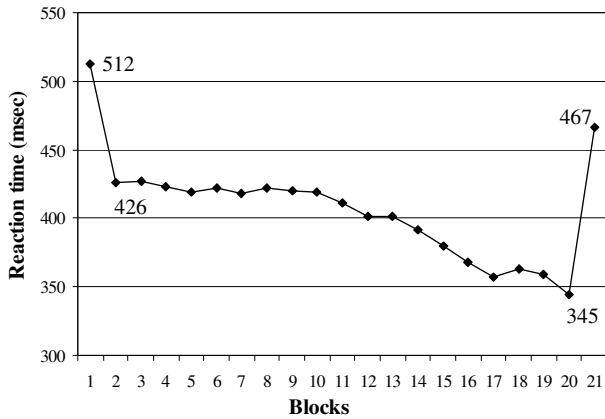


Figure 4: The average of reaction times by blocks in the SRT task

**Probabilistic classification learning (PCL)** As input variable for the data analysis of the PCL method, we used the average of the correct answers within each of the blocks. Figure 5 shows the average percentage of the participants' correct answers during the 5 blocks of the task.

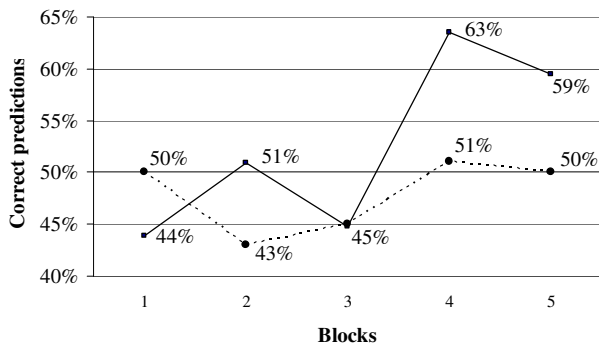


Figure 5: The average percentage of correct answers during the 5 blocks of the PCL task; the continuous line shows the task with hidden rule, the broken line shows the task without hidden rule

As can be seen on the graph, during the first 3 blocks the participants stayed at chance level [ $t(39)=0.77, p>0.1$ ], which shows that they blindly guessed the outcome. On the other hand, in the last two blocks they performed significantly above chance level. To demonstrate the difference in Figure 5, we indicated the percentage of correct answers on a task without hidden rule, where the outcomes followed the geometrical sets by chance (Aczél, 2003). There is a significant difference between the percentage of the correct answers in the first three and the last two blocks:  $t(39)=-4.1, p<0.001$ . The number of correct answers in the last two blocks also shows a significant increase from chance level:  $t(39)=4.5, p<0.001$ . On the basis of these results we can

declare that the participants learned the hidden rule similarly to the preceding studies.

**Input Data for the Cross Correlation** To test the main question we had to define the exact implicit learning variable for each method, which we could then compare. We used the indicator variables developed by Gönci (2004) in an earlier study examining methodological problems of the implicit learning procedures. As the standard indicator of implicit learning in AGL studies we used the percentage of correct answers in the grammar prediction phase. The higher the percentage, the higher the participant's implicit learning. In the PCL task the variable for measuring the implicit learning was the difference between the average of correct answers in the first three, and the average of correct answers in the last two blocks. This variable showed the increase of correct answers during the task, which increase is explained by the implicit learning of the participant. In the SRT task the indicator variable was the difference between the average of reaction time in the 21st and the 20th block. The difference occurred, because of the change in the hidden pattern. The higher the difference, the higher the effect of the implicit learning on the reaction speed of the participant. We used these variables due to their strong differentiating power.

**Cross Correlation Results** As Table 1 shows, there is no significant correlation among the three variables. Since the three methods do not have a common measuring variable, we also tested the correlation of the order of the performance of the participants in the three tasks, but we could not find significant correlation either (see Table 1).

Table 1: Correlation of the performances and of the order numbers on the three tests

Cross correlations	r	p
AGL – SRT	0.16	>0.1
AGL – PCL	-0.23	>0.1
SRT – PCL	-0.03	>0.1
Correlation of orders	r	p
AGL – SRT	0.02	>0.1
AGL – PCL	-0.21	>0.1
SRT – PCL	-0.01	>0.1

## Discussion

In this study we made a purposeful methodological examination about the three main methods of implicit learning. We experienced in the relevant literature a convertible application of these tests for measuring this kind of learning phenomenon. The question that we wanted to answer was whether these frequently used paradigms could be applied to the same phenomenon of memory and learning, or if the constructional and instructional components of the tests make different relevance to them. We assumed that, if these methods measure a certain property of the learning

system of a person then these tests should behave more consistently intrapersonally than interpersonally.

The three implicit learning measuring methods (AGL, SRT, PCL) were used with 40 healthy persons individually. The tests were administered within one session in varying order. The order of the tests did not cause significant difference in the performance. In all cases we found the expected implicit learning rates comparable to the previous studies. In this respect it is grounded to generalize our result to the previous experiments using the same methods.

The statistical analysis, examining the cross validity of these tests showed no significant correlation among the implicit learning indexes. This result suggests that one person's performance on one implicit learning test has nothing to do with his/her performance on another implicit learning test. The lack of correlation is quite unexpected, if we intend to think about implicit learning as an undivided cognitive ability. It is also surprising if we consider that the studies examining the features of implicit learning based their conclusions on various methods. Thus we should rather ask, 'what do these tests have in common?' As described in the introduction, the most common definition of implicit learning is a process, when we acquire new information without intending to do so, which can have an effect on our decisions and behavior. All of the methods we tested suited this criterion. So what is the reason of this oddity? Here we briefly discuss our possible explanations, approached from two aspects and we propose some possible ways for further research.

**Unity or fractionality** Regarding the results, the question arises of whether this unitary view about an undivided implicit learning phenomenon is still supportable, or not. In the later case, if these methods measure validly non-conscious learning processes, we should hypothesize that implicit learning is segmentalized into various partitions. From the point of view of the question of unity or fractionality, the outcome of this validation study supports the rejection of the idea of the classical conception. Further, this supports the view that all of these tasks can be associated to different segments of an embracing concept of implicit learning.

**Process analysis** We found the above projected approach though rational, but still far from a viable model. The understanding of the phenomenon seems to be more expedient through a process analysis. Therefore we took our thinking further on Stadler and Roediger's proposition about nature of encoding and retrieval in the case of learning tasks (1998). Table 2 shows our hypothetical matrix of memory processes completing Stadler and Roediger's description.

It comes from the operational definitions of implicit learning and implicit memory (Bowers & Marsolek, 2003) that its components can be combined in various ways (implicit encoding with implicit retrieval; implicit encoding with explicit retrieval; explicit encoding with implicit

retrieval; and explicit encoding with explicit retrieval) <sup>1</sup>. Probabilistic learning (PCL) varies so much from the other two tests (e.g. not deterministic) that we did not try to couple it with the others.

Table 2: Hypothetical division of implicit and explicit memory tasks from a process-based regard.

		Encoding	
		Implicit	Explicit
Retrieval	Implicit	SRT	Implicit Memory
	Explicit	AGL	Explicit Memory

This alterity of the tests could be a reasonable explanation of our results and thus the methods would still measure the same phenomenon, but from a different aspect. In the context of this matrix, a new thinking may begin to explore the relations of these processes in learning. To test this hypothesis, other tests, fitting the same box of the matrix are planned to be examined together.

It is evident that implicit learning may interact with explicit learning and other cognitive processes in many complex ways. In this respect this model may seem to oversimplify the question of the entangled issue of implicit research. However, we still believe that a thorough examination of this process-based regard is essential for the understanding of these ways of learning.

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<sup>1</sup> We have to remark at this point that in the case of implicit learning the nature of encoding and retrieval refers to the nature of the instruction only, braver surmises would open here intense debates.

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