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Implicit and Explicit Learning: Individual Differences and IQ

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We explored the degree to which individual differences in performance were observed in a group of subjects who worked with two different tasks: one implicit and one explicit. The implicit task was a standard artificial grammar-learning task; the explicit was a series-completion problem-solving task. Substantial individual differences were found between subjects on the explicit task; relatively small individual differences were found on the implicit task. Moreover, performance on the explicit task correlated strongly with intelligence quotient, but performance on the implicit task did not. Data from previous experiments were also found to be in agreement with these results. The findings are presented in the context of a general theory of implicit learning proposed recently by Reber (1989a, in press) that derives from considerations of the evolution of cognitive processes. This evolutionary model argues that unconscious, implicit induction systems are evolutionarily older and antedate conscious, explicit learning processes, and that this antiquity carries with it particular patterns of function that differentiate implicit processes from explicit processes.

As generally characterized, implicit learning is the process whereby a complex, rule-governed knowledge base is acquired largely independently of awareness of both the process and the product of the acquisition. In a series of recent articles, Reber (1989a, 1989b, 1990, in press) presented a general overview on the literature on implicit cognitive processes, and outlined several extensions of the work on implicit learning and implicit memory. The argument made in those articles is that implicit, unconscious, cognitive processes need to be viewed within the context of the adaptationist principles of evolutionary biology, and seen not just in descriptive terms but in terms of ontogeny, phylogeny, and function.

The basic premise is that of the primacy of the implicit. The unconscious processes, which have become known in the literature as implicit learning (Reber, 1989a) and implicit memory (Schacter, 1987), are the functional instantiations of a phylogenetically primitive system that developed before the emergence of conscious functioning. The assumption that these structures and the functions they subsume have phyletic primacy has a number of implications concerning the manner in which implicit and explicit functions are dissociable. Implicit systems can be expected to display properties that would differentiate them from overt, conscious, cognitive processes such as problem solving, decision making, recognition and recall from short- and long-term memory, apprehension of self, the monitoring of reality, and so on. Among these properties are (a) that implicit systems should be robust in the face of various psychiatric or neurological insults, which compromise functioning of the more traditionally examined explicit cognitive operations; (b) that implicit systems ought to display tighter distributions in the population when compared with explicit systems; fewer individual differences and smaller population variances are to be expected when comparing the covert and unconscious with the overt and conscious functions; and (c) that implicit functions should operate largely independently of standard measures of cognitive capability such as intelligence, assuming that intelligence is being measured using traditional psychometric instruments, that is, an intelligence quotient (IQ) test.

These points of departure between the conscious and the unconscious can be formally derived from some relatively simple principles of evolutionary biology. Such a derivation is dependent on the recognition that early appearing forms and structures display classes of properties that distinguish them from later appearing forms and structures and von Baer's (1828) classic principle that development proceeds from the general to the specific. See Schank and Wimsatt (1987) and Wimsatt (1986) for the formal model and Reber (1990, in press) for details on how it is used to derive these and various other principles.

There is a substantial body of evidence in support of the first of these propositions. With respect to implicit memory, large-scale reviews of the clinical and cognitive literatures uncovered scores of cases where a strong memorial element exists and plays an important causal role in behavior independent of the patient's conscious apprehension of these memories (see Schacter, 1987; Shimamura, 1990). This memorial asymmetry has been found in patients with disorders ranging from the classic cases of amnesia induced by bilateral hippocampal lesions (Milner, Corkin, & Teuber, 1968) to prosopagnosia (Bauer, 1984; DeHaan, Young, & Newcombe, 1987; Young & DeHaan, 1988), alexia (Shallice & Saffran, 1986), blindsight (Weiskrantz, 1986), and even multiple personality disorders (Nissen, Ross, Willingham, Mackenzie, & Schacter, 1988).

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Parallel support comes from a number of other tasks that involve not just implicit memory for past events but the implicit acquisition of new information. Hasher, Zacks, and their colleagues' work on automatic frequency encoding (see Hasher & Zacks, 1984, for a review) is illustrative. This automatic, implicit process has been shown to be robust in the face of clinical depression (Hasher & Zacks, 1979) and Korsakoff's syndrome (Strauss, Weingartner, & Thompson, 1985). Along similar lines, Knopman and Nissen (1987), using sequentially ordered patterns, reported implicit learning in patients whose cognitive functions are severely compromised by probable Alzheimer's disease. Johnson, Kim, and Risse (1985) presented Korsakoff's disease patients and normal subjects with repeating melodies from traditional Korean songs. Later both groups of subjects were asked to give preference ratings for both new melodies and ones presented earlier. Both groups showed the same preferences for previously presented melodies, although only the normal subjects showed conscious memory for them. Finally, Abrams and Reber (1988) reported implicit learning in severely disabled psychiatric patients with a range of disorders from schizophrenia to chronic alcoholism with probable organic brain damage. In this study, patients displayed implicit functioning with the underlying structure of an artificial grammar that was indistinguishable from that of a group of normal controls. However, the psychiatric patients showed severe deficits when required to work with relatively simple problems that required conscious rule learning to discover solutions.

In summary, there seems to be no question about the robustness of implicit processing systems when compared with explicit processing systems. Unconscious processes clearly show greater resistance to insult and injury than do conscious processes. The data base here is still relatively new and liable to reinterpretation, but the available evidence is highly consistent with the evolutionary model of implicit processes.

The support for the other two hypotheses is not as easy to come by. There has been surprisingly little work that addresses these issues directly, probably because they are not obvious entailments of any other current theory of cognition. Consequently, it is toward these that this article is primarily oriented.

With regard to the second hypothesis concerning individual differences, what evidence exists is consistent with our findings just discussed. The work of Hasher, Zacks, and their colleagues has yielded most of the relevant findings. Zacks, Hasher, and Sanft (1982) reported no differences on frequency encoding between students from a university with median Scholastic Aptitude Test (SAT) scores of 610 and those from a school with median SAT scores of 471. In other studies, factors such as chronological age (Hasher & Chromiak, 1977) and overall classroom performance of students (Goldstein, Hasher, & Stein, 1983) were shown not to differentiate between subjects. Because Hasher and Zacks also drew on evolutionary considerations as a basis for developing their model (Hasher & Zacks, 1984), these findings are of particular interest.

The issue of individual differences, of course, connects closely with the third proposition concerning the relationship between implicit processes and intelligence. The literature on the topic, however, has focused more on the question of the relationship between performance on implicit tasks and intelligence as assessed by standard IQ tests than on the degree of individual variation. The issues are problematical for several reasons including the lack of agreement about just what intelligence is, what it relates to in terms of performance in real-world settings, and what methods should be used to evaluate it.

Before the development of psychometric techniques, intelligence was viewed as the ability to profit from experience and the ability to adapt to and function successfully within a given environment. With the development of a sophisticated psychometrics, the concept became inextricably linked with the techniques used in its measurement. Initially, Spearman (1904) represented human intelligence as a single general factor (*g*), which he assumed influenced all aspects of human cognition and overall functioning. Early factor-analytic techniques were developed to reveal the degree to which correlations between the various subtests on an intelligence test could be attributed to specific abilities (which Spearman believed to be acquired through training) and the degree to which they could be shown to reflect the operations of *g* (which he believed to be primarily inherited).

Most other theories of intelligence have sought to define intelligence as an aggregate of factors or abilities or both. Inherent in the classic theory of multiple intelligences is the notion that some components of these intelligences are included in the IQ score, whereas other components are not. First suggested by L. L. Thurstone, the model has led researchers to formulate theories that identify a stunning range of, in principle, distinguishable intelligences, from 7 separate intelligences (Gardner, 1983) to perhaps 150 (Guilford, 1977). In addition, Sternberg (1985) introduced a triarchic theory, which maintains that three important subtheories are needed to form a complete theory of intelligence. These subtheories emphasize the importance of taking into account contextual or cultural biases, the ability to perform automatic functions so as to be able to deal efficiently with novel inputs, how basic cognitive processes such as encoding operations are organized, and how new procedural knowledge is acquired. Sternberg specifically argued that many people are more successful in real-world settings than would be expected on the basis of their scores on standard IQ tests (Sternberg, 1985, 1986).

Working within this general approach, there has recently been an attempt to differentiate between the overt academic-type intelligence such as that typically found in IQ tests and the more covert, abstract-type intelligence found in natural settings. This work is directly relevant to the third hypothesis. Some of the descriptions of the covert, abstract kinds of intelligent functioning seem to touch on the way in which implicit learning and tacit knowledge have been traditionally described.

Ceci and Liker (1986a) differentiated between what they termed *academic intelligence* and *nonacademic intelligence*. They contended that each represents an underlying capacity whose primary function is to acquire knowledge, detect the relationships that exist between elements of the environment, and monitor ongoing cognitive processes, in particular domains. Put simply, people should be able to adapt to and function successfully in a given context. According to Ceci and Liker, IQ reflects academic-type knowledge and skills; it does not necessarily relate to general intellectual capacity. This characterization seems vaguely familiar; indeed it is quite close to the way in which the prepsychometricians thought of intelligence.

In a recent study designed to explore this general framework, Ceci and Liker (1986b, 1988) examined the relationship between IQ as measured by a standard test—Wechsler Adult Intelligence Scale-Revised (WAIS-R)—and a complex cognitive task that is not one typically associated with academic performance: horse-race handicapping. They studied two groups of subjects: one made up of expert handicappers and the other nonexpert handicappers. They found that virtually all of the experts used a complex mental model with multiple interactions, whereas less than one third of the nonexperts used similarly abstract cognitive processes. These sophisticated cognitive processes that underlie the handicapping skills were, however, uncorrelated with IQ, leading Ceci and Liker to conclude that the IQ tests were not measuring this particular capacity for complex cognitive reasoning.

Further support for this general model comes from Wagner and Sternberg (1985, 1986), who differentiated between practical (or tacit) intelligence and academic (or explicit) intelligence. They claimed that the type of knowledge used for success in most real-world settings is of the practical, tacit kind. Academic intelligence is formal, and is evaluated primarily by tasks usually found on mental ability tests and in academic settings; tacit knowledge is practical, informal, and usually acquired indirectly or implicitly. In addition, they argued, because much tacit knowledge is loosely organized and relatively inaccessible, the implicit type of knowledge may not lend itself to being directly taught.

In a recent study of practical intelligence, Wagner and Sternberg (1985) focused on the relationship between tacit knowledge and professional expertise. They found that although the kinds of tacit knowledge people generally pick up on the job correlated moderately with established criteria for professional success, there was no relationship with general intelligence when measured by a standard test of verbal reasoning.

Tacit and abstract components of cognitive functioning appear to operate largely independently of the overt and conscious and, moreover, do so independently of standard measures of intelligence. This fits, of course, with our third proposition. Implicit learning, as it has been studied in the laboratory, appears to be abstract and not reliant on formal learning and, as such, seems to relate closely with the nonacademic knowledge described by Ceci and Liker (1986a) and the practical intelligence of Wagner and Sternberg (1986).

Given all of this, there is a clear need for a better understanding of the manner in which implicit cognitive processes can be differentiated from the explicit and to begin to build a data base that can be used to examine these relationships. The following experiment was designed with two considerations in mind: (a) to explore the question of individual variation in functioning on two tasks—one traditional implicit learning task and one compellingly explicit task—and (b) to evaluate the degree to which performance on both of these tasks covaries with intelligence as measured by a standard instrument.

Method

To perform the comparison, two tasks were needed that were superficially similar to each other but where one task clearly tapped implicit processes, whereas the other unambiguously recruited explicit processes. The implicit task used was the now standard artificial grammar-learning experiment; the explicit task was a series-solution task based on alphabetical stimuli.

Grammar Learning

In this procedure, subjects are presented with a learning set of exemplary letter strings generated by a synthetic, semantic-free grammar. The grammar used here is shown in Figure 1. After learning, subjects' knowledge of the rules of the grammar is evaluated by a well-formedness task during which they are asked to determine the grammatical status of a set of letter strings, some of which conform to the rules of the grammar and some of which contain violations of those rules. There is a large literature on this paradigm showing that it is a near optimal technique for obtaining implicit learning, and that the knowledge base it yields is predominantly tacit in nature (see Reber, 1989a, 1989b).

Series Solutions

In this procedure, subjects are presented with a set of ordered sequences of letters, each representing a different discernible pattern that must be discovered. Subjects are tested on their solutions with a two-alternative, forced-choice (2AFC) procedure in which they have to select the correct continuation of the sequence. This task is a compellingly explicit task in which subjects use conscious code-breaking and problem-solving strategies. As such, it represents the opposite pole from the implicit, grammar-learning technique, although it has the required superficial resemblance to the implicit task in that in both tasks the stimuli consist of strings of letters whose order is given by a complex set of rules.

Individual Differences

Determining whether some trait x has a different distribution in the population than some other trait y is a complex psychometric problem. Initially, one has to be able to show, with reasonable certainty, that a common metric exists along which both traits are being measured. It does not make sense, for example, to try to answer a question such as, "What shows greater variance in the population, height or weight?" because there is no common basis in measurement between the two variables to make such a comparison sensible. In

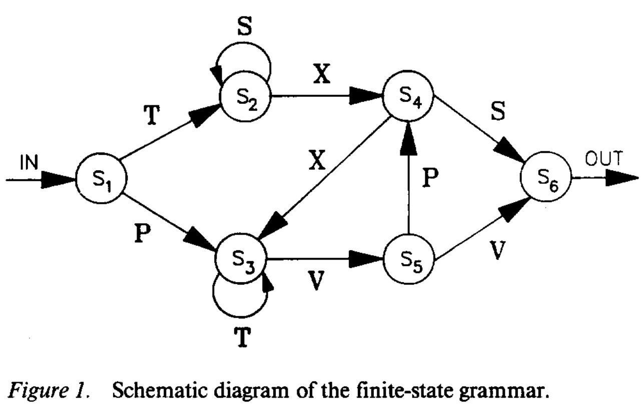

Figure 1. Schematic diagram of the finite-state grammar.

any event, such questions are typically not asked simply because everyone assumes that traits like these are normally distributed in the population and questions of variance do not even get raised.

However, one of the key hypotheses of implicit learning theory is that implicit cognitive processes will show a tighter distribution in the population than explicit cognitive processes. To test such a hypothesis, one needs some procedure for measuring implicit and explicit processes so that their underlying metrics can, for the purposes of the experiment, be regarded as comparable. Our technique was to use a two-choice procedure on both the implicit and explicit tasks and to develop stimulus materials of comparable difficulty so that the means of distributions of correct responses on the two tasks were statistically indistinguishable. This technique is, of course, not psychometrically ideal, but it is pragmatically powerful and, as we point out later, provides important evidence on the question at hand.

Intelligence and IQ

We took a similarly pragmatic stance on the question of what intelligence is and how it relates to standard measures of IQ. One way of viewing the purposes of this experiment is as an exploration of the relationships between four factors: implicit learning, explicit processes, IQ, and intelligence. We have procedures for measuring each of these except the last, although for the better part of our history we have assumed that IQ was a measure of intelligence. However, as discussed previously here, various forms of intelligent behaviors are displayed by individuals who might not be expected to be capable of such behaviors if IQ scores from standard tests are taken as diagnostic. For our purposes, we regard intelligence separately from a score on an IQ test, and our concern is to assess the manner in which intelligent behaviors (the performance on the two tasks) covary with IQ. Measures of IQ issues were handled in a straightforward manner; all subjects were administered four subtests of the WAIS-R, and their combined score was taken as a measure of IQ.

In summary, the method here was to present all subjects with two tasks: one implicit and one explicit. These tasks were shown to be statistically indistinguishable in difficulty and thereby comparable for purposes of this experiment. Performance on the two tasks was compared to evaluate the distribution in the sample studied and to determine the extent to which each corresponded with a standard measure of IQ.

Subjects

A single group of 20 subjects—all undergraduates at Brooklyn College—participated in all aspects of the experiment, which was part of a course requirement. Order of the two tasks was counterbalanced; half of the subjects received the explicit task first and half the implicit task first.

Implicit Task

Stimuli. There are 43 grammatical (G) letter strings between the lengths of 3 and 8 letters that can be generated by the grammar in Figure 1. Twenty were used as learning stimuli. They were selected so that all the variations of the grammar, the three loops, and all possible beginnings and endings were displayed. The testing stimuli consisted of 25 G letter strings (7 of which were old strings from the learning set) and 25 nongrammatical (NG) letter strings, which were formed by introducing one or more violations into otherwise G letter strings.

Learning. Learning consisted of having subjects memorize each of the 20 exemplars. The letter strings appeared on a computer screen, one at a time for 3 s. After the string went off, the subject was prompted to reproduce it by typing it on the keyboard. If the letter string was reproduced correctly, the subject was so informed and a new letter string was presented. If an error was made, the subject was asked to try again and the letter string reappeared. All 20 exemplars were presented twice for a total of 40 learning trials. Subjects were not told anything at this point about the rule-governed nature of the letter strings; the instructions described a simple memory experiment.

The acquisition phase of an implicit learning experiment actually has significant explicit elements to it. As pointed out elsewhere (Reber, 1989a), the demands of the memorization task invite subjects to develop often rather elaborate mnemonic devices and, as shown later here, these explicit elements of the task will display properties similar to the overtly explicit problem-solving task. The implicit element in this task is the induction of the tacit knowledge base, which is used to make decisions during the testing phase.

Testing. At the beginning of this phase of the experiment, subjects were informed that the letter strings they had just learned were in fact formed according to a complex set of rules, and that they would now be tested on their knowledge of those rules. The testing phase used a well-formedness task, which consisted of giving subjects the full set of 50 test letter strings, one at a time. Each letter string appeared on the screen, and subjects were told to respond "yes" (by pressing the Y key) or "no" (N key) depending on whether or not they felt that the string conformed to the rules of the grammar. The entire set was presented twice so that 100 well-formedness judgments were made by each subject. Subjects were not informed about the correctness of their choices, and were not told that each test string was presented twice.

Explicit Task

The explicit task used the pool of 21 series-solution problems given in Table 1. Ten of the problems are alphabetic and 11 are nonalphabetic. An alphabetic series is one where the solution is dependent on movement through the alphabet; nonalphabetic series are solved without regard to such sequencing. For example, in the alphabetic series ABCBCDCDE__, the sequence is broken into chunks of three,

Table 1
Series-Solution Problems

Letter string	Next letter choice	
Alphabetic series		
ABCBCDCDE__	D[a]	C
ABBBBBCBBD__	B[a]	C
ABABBACBAD__	A	B[a]
AABABC__	B	A[a]
ABCDABCA__	D	B[a]
ABCDBCCDEC__	D[a]	B
ABCBBCC__	A	B[a]
AABBABCBACDBA__	D[a]	C
ACBDCE__	D[a]	B
Nonalphabetic series		
CDEADCA__	E[a]	D
CDAADCFBEE__	F	B[a]
ABCDEDEC__	B	A[a]
AEFEFAFAE__	A[a]	E
DDEFDEEFDE__	E	F[a]
AFDDAFFDA__	A[a]	F
CDEFCEDFC__	D[a]	E
CDECEDECDE__	D[a]	C
ABCADEACBA__	D	E[a]
DEAFEDAFEA__	D[a]	F
ABCDDCBAABCCBA__	C	A[a]

[a] Correct choice.

ABC-BCD-CDE-__; each chunk begins with the next letter in the alphabet after letter that initiated the previous chunk. The nonalphabetic problem CDBADCA__ is a two-letter mirror-image series in which the letters are arbitrary but successive sets of letters, each of which is mirror image of an earlier set (i.e., CD, BA, DC, A__). The two kinds of problems were used to keep subjects from forming simple solution sets.

Twelve series-solution problems were selected at random for each subject. Each series appeared on the computer screen along with two letters, one of which was the correct solution. Subjects typed their answer on the keyboard. The letter string and the two choices remained on the screen for a maximum of 1 min or until the subject responded. If a full minute passed, the letter string disappeared and the subject was asked simply to guess. After each problem, the subjects were asked to give as full an explanation as possible of why they chose the solution they did. Subjects were not informed about the correctness of their choices, nor were they told about the two different kinds of problems.

IQ Testing

After these two phases of the experiment were completed, all subjects were given four subtests from the WAIS-R. The subtests used were Picture Arrangement, Vocabulary, Block Design, and Arithmetic. These four subtests have been shown to correlate highly with the original full-length version of the WAIS-R, with values from .92 (Brooker & Cyr, 1986) to .96 (Doppelt, 1956) reported. The abbreviated version took approximately 40 min to administer.

Results

The most efficient way to view the data is to examine each of the tasks separately and then study the comparisons between them.

Grammar Learning

Acquisition. With experience, subjects became increasingly effective in memorizing letter strings. The mean number of errors made before correctly reproducing a letter string, broken into four blocks of 10 items each, was 2.64, 2.28, 1.69, and 1.58. This drop-off in errors shows that subjects were learning to exploit the structure inherent in the exemplary strings, a result which has been reported in all previous artificial grammar-learning studies (see Reber, 1989a).

Well-formedness testing. Table 2 gives the number of G and NG responses to G and NG items for all subjects. The mean percentage of correct judgments (P_c) was .609 (SD = 7.2), which is significantly above chance, $t(19) = 6.38$, $p < .01$, indicating that subjects are able to use the knowledge from the learning phase to identify the G status of novel test strings. Subjects showed a slight bias to classify letter strings as G even though they were informed that exactly half of the strings would be acceptable and half not. This result has been observed in other studies and is not particularly troublesome.

Table 2
Number and Proportion of Grammatical (G) and Nongrammatical (NG) Responses Given to G and NG Items on the Well-Formedness Task

	Number of responses			Proportion of responses		
Response	G	NG	Total	G	NG	Total
G	643	426	1,069	0.322	0.213	0.535
NG	357	574	931	0.178	0.287	0.465

There was some evidence that the knowledge base that subjects took from the learning phase was not as neatly representative of the synthetic grammar as is typically observed (see Reber, 1989a). A useful measure of representativeness is the degree of consistent responding to test strings. Each letter string on the well-formedness task is presented twice, and subjects may classify it correctly (C) or erroneously (E) on each presentation. If each subject's tacit knowledge base is a partial but accurate reflection of the underlying rules of the grammar, then we should observe roughly the same number of items with the pattern EE as with EC and CE. The reasoning here is based on the presumption that when subjects do not know the status of a particular item (i.e., their knowledge base, partial as it must be, does not encompass that item's properties) then they simply guess. However, a value of EE in excess of EC and CE implies the use of nonrepresentative rules in that subjects are making consistent errors on particular letter strings. The observed values for CE, EC, and EE were .17, .14, and .24, respectively, which suggests that subjects were introducing some nonrepresentative rules. There was a slight tendency for the EE values to be higher among subjects who performed the explicit series-solution task first (.26 vs. .22), although this difference fell short of significance.

Series Solutions

The mean percentage of problems solved correctly (P_c) was .61 (SD = 15.41), which was significantly above chance, $t(19) = 3.21$, $p < .01$. Our intention was to have this value be close to the proportion correct on the well-formedness task in the implicit phase. Indeed we seem to have done our job here almost too well. The means on the two tasks are virtually identical, which, if nothing else, shows that Murphy can occasionally work in behalf of the honest researcher. The more similar the means, the stronger the case for performing the comparison between variances presented next.

Task Comparisons

Task order. There were no significant order effects. Although there were hints that the implicit task was handled in a somewhat less implicit manner by subjects who had been run through the series-solution task first, from a strictly statistical view neither task benefited or suffered from being administered first or second. Hence, all analyses were carried out collapsed over order. There are two key comparisons between these two tasks: one that examines individual differences and one that studies the concordance between performance and IQ.

Individual differences. This analysis is sufficiently close to statistical legerdemain that some arguments are needed to support its legitimacy. We want a strong test of the prediction that implicit processes show fewer individual differences than explicit processes. However, as noted previously here, such a comparison cannot properly be made without showing that both processes are being measured using a common metric. The goal here was to develop a set of circumstances that had the effect of forcing such a metric. First, all subjects were run through both procedures so that the scores on both tasks are taken from the same sample. Second, the use of a 2AFC procedure on both tasks yields measures of performance on both tasks that are binomial. Third, the tasks were of equivalent difficulty. Fourth, and most important, these empirical techniques are supported by the fact that the rationale for the comparisons between the sample variances is deeply theory driven. Hence, we are comfortable with the following analysis and accept the results as a real finding.

A simple heterogeneity of variance test was performed on the sample P_c scores from the two tasks. The result is quite compelling: The distribution of scores from the explicit task shows dramatically greater variance than that from the implicit task ($F_{max} = 4.54$, $p < .01$). The ranges were also interesting; we observed values of P_c from .33 to .92 on the explicit task but only from .46 to .73 on the implicit task. Clearly, the implicit task shows relatively little in the way of individual-to-individual variation in performance, whereas the explicit task shows a considerable range of performance.

Performance and IQ. For these analyses, the four subtests from the WAIS-R were converted to full IQ scores using Doppelt's (1956) procedure. The mean IQ was 110 (SD = 21.2). The mean is about what one would expect from a group of college students. The degree of variability is somewhat higher than expected, and the range showed surprising extremes from a high of 151 to a low of 73.

The prediction was that implicit and explicit tasks should show different degrees of concordance with IQ. Specifically, given the nature of standard tests of intelligence, there should be strong correlations between subjects' IQs and their level of performance on the explicit problem-solving task but little or no such relationship between IQ and performance on the implicit task.

The results were in keeping with this pattern. IQ correlated strongly with P_c on the explicit task ($r = .69$, $p < .01$) but nonsignificantly with P_c on the well-formedness task ($r = .25$, $p > .05$), and these two correlations are significantly different from each other ($p < .05$). Levels of performance on the two tasks were uncorrelated ($r = .32$, $p > .05$). It is worth noting that these nonsignificant correlations are nowhere near zero. Were these degrees of concordance to be maintained with an increased sample size, they would become statistically significant. The point is not that there is no concordance between the implicit systems and IQ, but that the correlations will be lower than those between the explicit and IQ. Both the implicit and the explicit tasks have adaptive value for an organism, but the implicit task is constrained by virtue of its evolutionary antiquity.

One concern here is that the correlations between the implicit task and the two other factors might be low merely because of the restricted range on the scores of the implicit task. That is, the correctness of the first of our predictions (relatively small individual differences on implicit tasks relative to explicit tasks) might be driving the apparent correctness of the other predictions (differential degrees of concordance between implicit tasks, explicit tasks, and IQ). The essential issue, however, is not whether the range of scores on the implicit task is small, but whether it is, by virtue of some aspect of our procedure, truncated. There is no problem in finding correlations between factors with small ranges of scores provided that those scores are indeed reliable reflections of the underlying distribution. To examine this possibility, a Cronbach α on the items from the well-formedness part of the implicit learning task was run. Generally speaking, a Cronbach α above .4 or .5 is taken as reasonable support for the internal reliability of a test. We found an α of .51, which indicates that the well-formedness test is a reliable instrument and one that agrees nicely with that obtained by Dienes (1990) using a similar procedure.

Such a value argues that we can have confidence in the reliability of our observed individual differences, and that the observed patterns of *r*s are unlikely to be due to attenuated or truncated variance in the implicit task. That is, our observed variance is not attenuated in the sense that the real variance is actually large and our procedure somehow squeezed it down; it is small because the underlying factor being assessed actually shows little in the way of individual variation.

Finally, we examined the relationship between performance on the learning phase of the grammar task and IQ. As we pointed out previously here, because that task is at least partly a rote memory task and has shown a tendency to be coordinated with other forms of explicit functioning (Abrams & Reber, 1988), it should show concordance with other explicit tasks. The correlation between mean trials to criterion and IQ was less than that found with the series-solution task, but it was significant ($r = .46$, $p < .05$).

A Posteriori Analyses

Because the approach to implicit learning that we have taken here is new, there is little supporting evidence in the literature. To determine if corroboration can be found elsewhere, we unearthed the data from three earlier experiments, all of which were run originally to test other hypotheses concerning implicit learning. The data that are relevant here are those from studies that manipulated the instructional set under which subjects were run. In these experiments, subjects were run on an artificial grammar-learning task under either an implicit instructional set, in which they were told only that they were in a memory experiment (as in the current experiment), or an explicit instructional set, in which they were informed about the rule-governed nature of the stimuli and encouraged to try and figure out the rules for letter order. If our arguments concerning the patterns of individual variation in performance hold, we expect to see larger individual differences among subjects who were under the explicit instructional set than those working under an implicit set.

The three studies containing relevant data are by Reber (1968, 1976) and Rathus, Kushner, and Reber (1990). In each case, we compared the number of trials to criterion on the learning phase and ran an F_{max} test on the variances from the two groups. The data are given in Table 3. As can be seen, all three are in the predicted direction, although the F_{max} statistic fell short of significance on one. Note that the proper analysis here is on the learning-phase data and not the testing-phase data. As we pointed out previously here, performance on the learning phase contains explicit components and is expected to be correlated with IQ. The testing phase is designed to explore the utilization of a tacit knowledge base and, hence, would not be expected to display the same large individual-to-individual variation. This point is explored further later.

Discussion

The results from this study and from the reanalyses of the earlier experiments are consistent with the characterization of implicit learning as a process of knowledge acquisition that occurs largely independently of conscious attempts to learn and that yields a knowledge base that is largely outside of awareness. They are also consistent with the evolutionarily based interpretation of implicit systems recently proposed. From this perspective, implicit processes, owing to their phylogenetic antiquity, will show less individual-to-individual variation than comparable explicit processes and, given the nature of standard psychometric techniques for measuring intelligence, will show lower correlations with IQ. Each of these points needs to be discussed in more detail.

The proposition that implicit cognitive processes should show a different distribution in the population than explicit, conscious processes is an entailment of one of the basic heuristics of evolutionary biology: Phylogenetically old systems display less variation than new ones. Systems and structures with considerable antiquity have shed the variability that characterizes evolutionarily newer systems and structures. This is one of evolution's strongest conservative aspects; the success of the existing forms, as evidenced by their antiquity, reflects the effectiveness of those forms. Variation in structure and form is the basis for evolutionary change; systems that have undergone little change show little individual variation. The point simply is that once an adaptive, functional system evolves, and, a fortiori, the system is broadly operational in diverse environments, there is no adaptive value in change (see Reber, in press; Schank & Wimsatt, 1987, for formalizations of this principle). From the perspective taken here, the evolutionarily and phylogenetically older implicit processes ought to show a tighter distribution of performance than the more recently emergent explicit processes.

Table 3
F_{max} Tests on Learning Data From Earlier Studies

Study	F_{max}
Reber (1968)	$F_{max}(9, 2) = 14.5, p < .01$
Reber (1976)	$F_{max}(9, 2) = 10.2, p < .01$
Rathus, Kushner, & Reber (1990)	$F_{max}(29, 2) = 1.3, p > .05$

Note. In all cases the larger variance is associated with the implicit condition.

Interestingly, this question of subject-to-subject variation in implicit learning has attracted attention recently but within a different framework, which has led to some misunderstandings. There have been several recent reports of considerable intersubject variability in synthetic grammar-learning tasks similar to the one used here (Dulany, Carlson, & Dewey, 1984, 1985; Mathews et al., 1989; McAndrews & Moscovitch, 1985). Dulany et al. (1984, 1985) characterized this variability as a tendency for individual subjects to develop personal "correlated grammars" that reflect particular aspects of the rule system of the synthetic language.

In our laboratory, we have also observed such idiosyncratic behaviors (see Reber, 1989a; Reber & Allen, 1978), but we view them differently. These eccentricities, however real they may appear, do not necessarily map into differential knowledge bases. Although individual subjects may pick up idiosyncratic components of a complex display, if what each picks up is reflective of the underlying rule system, it will yield relatively small subject-to-subject variation when subjects are called on to use their knowledge, for example, to distinguish well- from ill-formed strings. Moreover, as Servan-Schreiber and Anderson (1990) recently showed, much of the induction of knowledge base of one of these synthetic grammars can be accounted for by a general "chunking" operation whereby subjects group letters together to form larger units on the basis of the patterns of covariation displayed by the grammar. The individual differences thus prove to be rather superficial; the deep induction routines produce similar levels of usable, tacit knowledge.

This point is important because it has led to some confusion over the degree to which there is commonality in the processes involved in implicit learning. If one subject examines a complex display of letters and sees patterns that reflect, say, the initials of one's friends and another subject sees a code based on positions on a baseball diamond, these are individual differences but they are ones that do not make a difference. The use of heuristics such as these reflects the operations of conscious, explicit systems and, accordingly, we expect to find considerable individual variation. However, so long as each of the coding devices is a partial but accurate reflection of the underlying patterns of covariations between letters, each subject will induce equivalently powerful representations of the rule system and equally powerful decision-making routines for working with novel displays. The deep question of individual variability here is dependent not so much on surface variations of coding schemata but on the underlying representational form that emerges from them. Our findings are congruent with the general theoretical model here in that the key data, the P_cs on the well-formedness task, show small variance when compared with P_cs on the series-solution task.

The differing degree of concordance between IQ and performance on implicit and explicit tasks also lends credence to the general characterization of implicit learning as a process that operates largely independently of intelligence as assessed by such devices as the WAIS-R. The data base here is still small, particularly when viewed against the vast literature on intelligence and the psychometric struggles involved in its assessment. Nevertheless, we believe that the pattern of results displayed in this study is important and supportive of the model put forward by Sternberg and Wagner (Sternberg, 1985; Wagner & Sternberg, 1986) which emphasizes the need to distinguish between practical (implicit) intelligence and academic (explicit) intelligence. Standard instruments, like the WAIS-R, tap explicit intelligence, the kind that is recruited for solving problems like our series completion task. They do not provide assessments of the capacity for implicit induction, a skill which, as our results imply, is going to prove to be difficult to assess in any meaningful way because there is likely to be little in the way of population variation to use as the basis for evaluation.

Finally, these results fit with the third of the broad predictions of implicit learning theory concerning the robustness of evolutionarily old structures and processes. As mentioned previously here, there is a considerable data base to support this proposition and, because of the manner in which it is linked theoretically with the other two, the outcome of this study can be viewed as supporting the general model.

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