51 Schacter, D.L. *et al.* (1995) Brain regions associated with retrieval of structurally coherent visual information *Nature* 376, 587–590

52 Andreasen, N.C. *et al.* (1996) Neural substrates of facial recognition *J. Neuropsychiatry* 8, 139–146

53 Tulving, E. *et al.* (1996) Novelty and familiarity activations in PET studies of memory encoding and retrieval *Cereb. Cortex* 6, 71–79

54 Busatto, G. *et al.* (1997) A functional magnetic resonance imaging study of episodic memory *NeuroReport* 8, 2671–2675

55 Rugg, M.D. *et al.* (1997) Brain regions supporting intentional and incidental memory: a PET study *NeuroReport* 8, 1283–1287

56 Petrides, M., Alivisatos, B. and Evans, A.C. (1995) Functional activation of the human ventrolateral frontal cortex during mnemonic retrieval of verbal information *Proc. Natl. Acad. Sci. U. S. A.* 92, 5803–5807

57 Snodgrass, J.G. and Vanderwart, M. (1980) A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity *J. Exp. Psychol. Hum. Learn. Mem.* 6, 174–215

58 Fletcher, P.C. *et al.* (1995) Brain systems for encoding and retrieval of auditory-verbal memory: an *in vivo* study in humans *Brain* 118, 401–416

59 Buckner, R.L. *et al.* (1996) Functional anatomic studies of memory retrieval for auditory words and pictures *J. Neurosci.* 16, 6219–6235

60 Buckner, R.L. *et al.* (1995) Functional anatomical studies of explicit and implicit memory retrieval tasks *J. Neurosci.* 15, 12–29

61 Bäckman, L. *et al.* (1997) Brain activation in young and older adults during implicit and explicit retrieval *J. Cogn. Neurosci.* 9, 378–391

62 Blaxton, T.A. *et al.* (1996) Functional mapping of human memory using PET: comparisons of conceptual and perceptual tasks *Can. J. Exp. Psychol.* 50, 42–56

63 Grasby, P.M. *et al.* (1994) A graded task approach to the functional mapping of brain areas implicated in auditory-verbal memory *Brain* 117, 1271–1282

64 Andreasen, N.C. *et al.* (1995) I. PET studies of memory: novel and practiced free recall of complex narratives *NeuroImage* 2, 284–295

65 Andreasen, N.C. *et al.* (1995) II. PET studies of memory: novel versus practiced free recall of word lists *NeuroImage* 2, 296–305

66 Fletcher, P.C. *et al.* (1996) Brain activity during memory retrieval: the influence of imagery and semantic cueing *Brain* 119, 1587–1596

67 Schacter, D.L. *et al.* (1996) The role of hippocampus and frontal cortex in age-related memory changes: a PET study *NeuroReport* 7, 1165–1169

68 Prabhakaren, V. *et al.* (1997) Neural substrates of fluid reasoning: An fMRI study of neocortical activation during performance of the Raven's Progressive Matrices test *Cognit. Psychol.* 33, 43–63

69 Thompson-Schill, S.L. *et al.* (1997) Role of left inferior prefrontal cortex in retrieval of semantic knowledge: a re-evaluation *Proc. Natl. Acad. Sci. U. S. A.* 94, 14792–14797

70 Baddeley, A. (1992) Working memory: the interface between memory and cognition *J. Cogn. Neurosci.* 4, 281–288

71 Petrides, M. (1994) Frontal lobes and behavior *Curr. Opin. Neurobiol.* 4, 207–211

Implicit learning: news from the front

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Can we learn without awareness? While the current consensus is most likely to be 'no', there is, however, considerable ongoing debate about the role that consciousness plays in cognition and about the nature of consciousness itself. In this article, we review recent advances in the field of implicit learning, based on three perspectives: empirical findings (including neuropsychological evidence), methodological issues, and theoretical positions (including computational models). The overall picture that emerges is complex and reflects a field that is very much in flux: while it seems undeniable that cognition involves some form of unconscious processing, it is as yet unclear how to best separate conscious and unconscious influences on learning, and how to best think about the status of the 'cognitive unconscious'. We suggest that implicit learning is best construed as a complex form of priming taking place in continuously learning neural systems, and that the distributional knowledge so acquired can be causally efficacious in the absence of awareness that this knowledge was acquired or that it is currently influencing processing, that is, in the absence of metaknowledge.

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Implicit learning (IL) – broadly construed, the ability to learn without awareness – has been under investigation for over thirty years, but it is only recently, through a renewal of interest both in learning and in consciousness, that the phenomenon has attracted widespread attention[1–8]. According to one of the most common and conceptually neutral definitions of IL[9], learning is implicit when we acquire new information without intending to do so, and in such a way that the resulting knowledge is difficult to express. In this, implicit learning thus contrasts strongly with explicit learning (e.g. as when learning how to solve a problem or learning a concept), which is typically hypothesis-driven and hence

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Box 1. Implicit learning and language acquisition

The past few years have witnessed the emergence of increasing connections between implicit learning and psycholinguistics. This is perhaps not so surprising, in that language acquisition, like implicit learning, involves incidental learning conditions. Further, cogent use of language likewise does not require explicit knowledge of grammar. Recently, several authors have begun to explore this connection empirically. For instance, Saffran *et al.*[a] showed how incidental exposure to artificial language-like auditory material (e.g. *bupadapatubitutibu*…) was sufficient to enable both children and adult subjects to segment the continuous sequence of sounds they had heard into the artificial words (e.g. *bupada*, *patubi*, etc.) that it contained, as evidenced by their above-chance performance in a subsequent recognition test. Based on these data, Saffran *et al.* suggested that word segmentation abilities develop based on mechanisms that exploit the statistical regularities present in sequences of events, such as for instance the fact that the transitional probabilities of successive syllables are higher within words than between words. Saffran *et al.* rooted their interpretation of their findings in the implicit learning literature. The connection is obvious as soon as one recognizes that language acquisition, like implicit learning[b,c] is likely to involve, at least in part, incidental learning of complex information organized at different levels. Part of the convergence can also be attributed to the impact of computational modeling. For instance, connectionist models such as the Simple Recurrent Network (see Box 5, Fig.) have been extensively used with significant success in both domains[c–e]. In effect, the problems faced in both domains are quite similar: How to best extract structure from a complex stimulus environment characterized by ‘deep’ systematic regularities when learning is incidental rather than intentional. The answer, in both domains, appears to be best embodied by distributional approaches.

References

a Saffran, J.R. *et al.* (1997) Incidental language learning: listening (and learning) out of the corner of your ear *Psychol. Sci.* 8, 101–105

b Berry, D.C. and Dienes, Z. (1993) *Implicit Learning: Theoretical and Empirical Issues*, Erlbaum

c Cleeremans, A. (1993) *Mechanisms of Implicit Learning: Connectionist Models of Sequence Learning*, MIT Press

d Christiansen, M.H., Allen, J. and Seidenberg, M.S. (1998) Learning to segment speech using multiple cues: a connectionist model *Lang. Cognit. Process.* 3, 221–268

e Redington, M. and Chater, N. (1997) Probabilistic and distributional approaches to language acquisition *Trends Cognit. Sci.* 1, 273–281

fully conscious. While everyday life seems replete of examples of situations where we ‘know more than we can tell’[10], including language acquisition and use (Box 1) as well as skill learning in general, it has so far proven extremely difficult to provide a satisfactory definition for IL, let alone to provide clear empirical demonstrations of its existence and to establish exactly what its properties are. As a case in point, Frensch[11] lists as many as eleven definitions of IL in a recent review article – a diversity that is undoubtedly symptomatic of the conceptual and methodological difficulties facing the field.

Today’s controversies are rooted in the seminal studies of Reber[12], whose early work initiated a vast programme of empirical research that continues to expand and that has explored IL through a wide variety of experimental situations, most of which follow the basic design described in Box 2. Three main paradigms are currently prevalent (see Box 2): dynamic system control (DSC)[13], artificial grammar learning[12] (AGL) and sequence learning[14] (SL) tasks. Other paradigms include learning of conditioned responses[15], acquisition of invariant characteristics[16], or second-language learning acquisition[17,18]. IL research, in contrast to subliminal perception research[19], typically involves supraliminal stimuli and tasks which, in contrast to implicit memory research[20], require sensitivity to the structural relationships between stimulus items rather than to specific stimuli (see Box 3). Further, to minimize the influence of subject’s prior knowledge, most paradigms involve complex, semantically neutral and arbitrary stimulus domains.

The bulk of this research has produced a relative consensus on several characteristics that distinguish implicit from explicit learning, usefully summarized by Dienes and Berry[3]: IL (1) shows specificity of transfer, in that implicit knowledge tends to be relatively inflexible, inaccessible, and bound to the surface features of the material, (2) tends to be associated with incidental rather than with intentional learning conditions, and (3) tends to remain robust in the face of time, lack of attentional resources, and psychological disorder (in particular, the amnesiac syndrome, see Box 4). The field remains significantly divided, however, about the following three issues:

- To what extent does IL produce unconscious knowledge?
- To what extent is IL subserved by independent memory and processing systems?
- To what extent does IL produce abstract knowledge?

Early work has characterized IL as a process by which abstract knowledge of the regularities of some domain can be acquired unconsciously and automatically by incidental exposure to relevant instances, thus seemingly endowing the cognitive system with what has been called a ‘smart’ unconscious[21]. Perhaps unsurprisingly, such a radical proposal has generated considerable controversy, and several new perspectives about IL have therefore emerged over the past few years.

These new perspectives have been largely motivated by methodological concerns about both the purported unconscious and abstract character of knowledge acquired in typical IL situations. Thus, many recent studies have in fact reported associations between performance on IL tasks and conscious knowledge (see Shanks and St John[6]). Likewise, it now appears that simple associative learning or chunking mechanisms, rather than rule abstraction processes, are largely sufficient to account for performance in all three main paradigms[22–26].

Such findings have prompted many authors to question the existence of IL. For instance, Shanks and St John[6] conclude their critical review article with the statement that: ‘Human learning is systematically accompanied by awareness’, and suggest that implicit and explicit learning should instead be distinguished based on their information-processing

Box 2. Paradigms for implicit learning

Implicit learning situations typically involve three components: (1) exposure to some complex rule-governed environment under incidental learning conditions; (2) a measure that tracks how well subjects can express their newly acquired knowledge about this environment through performance on the same or on a different task; and (3) a measure of the extent to which subjects are conscious of the knowledge they have acquired. Three paradigms that follow this conceptual design have been extensively explored: artificial grammar learning (AGL), sequence learning (SL), and dynamic system control (DSC).

Artificial Grammar Learning (AGL)

In Reber's[a] seminal AGL study, subjects are asked to memorize a set of letter strings generated by a finite-state grammar (see Fig.). After this memorization phase, they are told that the strings follow the rules of a grammar, and are asked to classify new strings as grammatical or not. Typically, subjects can perform this classification task better than chance would predict, despite remaining unable to describe the rules of the grammar in verbal reports[b,c]. This dissociation between classification performance and verbal report is the finding that prompted Reber to describe learning as implicit.

Sequence Learning (SL)

In typical SL situations[d], participants are asked to react to each element of sequentially structured and typically visual sequences of events in the context of a choice reaction task. On each trial, subjects see a stimulus appear at one of several locations on a computer screen and are asked to press as fast and as accurately as possible on the corresponding key. Unknown to them, the sequence of successive stimuli follows a repeating pattern[d,e] or is governed by a set of rules[f] that describes permissible transitions between successive stimuli, such as a finite-state grammars[g] (see Fig.). Subjects exposed to structured material produce faster 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 verbalizable knowledge of the pattern.

Dynamic System Control (DSC)

In DSC tasks, subjects learn to control the computer simulation of an interactive system such as a sugar production factory or a simulated person[h]. Subjects are told about the state of output variables such as the amount of sugar output the factory produces, and their task is to reach and maintain a specific goal level of sugar output by manipulating inputs such as the number of workers in the factory. After each interaction, the resulting state of the system is computed by way of an equation that relates input and output variables. Typically, subjects can achieve a good level of control of the system even though they remain unable to describe precisely the rules of the system in post-experimental structured questionnaires.

References

a Reber, A.S. (1967) Implicit learning of artificial grammars *J. Verbal Learn. Verbal Behav.* 6, 855–863

b Reber, A.S. (1989) Implicit learning and tacit knowledge *J. Exp. Psychol. Gen.* 118, 219–235

c Reber, A.S. (1993) *Implicit Learning and Tacit Knowledge: An Essay on the Cognitive Unconscious*, Oxford University Press

d Nissen, M.J. and Bullemer, P. (1987) Attentional requirement of learning: evidence from performance measures *Cognit. Psychol.* 19, 1–32

e Reed, J. and Johnson, P. (1994) Assessing implicit learning with indirect tests: determining what is learned about sequence structure *J. Exp. Psychol. Learn. Mem. Cognit.* 20, 585–594

f Lewicki, P., Hill, T. and Bizot, E. (1988) Acquisition of procedural knowledge about a pattern of stimuli that cannot be articulated *Cognit. Psychol.* 20, 24–37

g Cleeremans, A. (1993) *Mechanisms of Implicit Learning: Connectionist Models of Sequence*, MIT Press

h Berry, D.C. and Broadbent, D.E. (1984) On the relationship between task performance and associated verbalizable knowledge *Q. J. Exp. Psychol.* 39, 585–609

characteristics. Likewise, Whittlesea and Dorken[8] (see also Neal and Hesketh[27]) have suggested that IL is 'just ordinary learning without becoming aware of the implications of that learning' and that IL research should therefore focus not on awareness, but on criteria such as the role of intention during learning or the congruence between task demands during learning and subsequent use of knowledge. Perruchet and Vinter[28] take consciousness to be constitutive of cognition while admitting that some learning processes (but not the representations they produce) can be unconscious.

Thus, in the space of a few years, our general perspective on IL has changed from one that assumes the existence of some potentially mysterious processes of passive, automatic, and unconscious acquisition of abstract and tacit knowledge to one that aims to highlight the fact that IL is merely a side-effect of ongoing processing, and that awareness systematically accompanies learning.

In this paper, we review these shifting perspectives by addressing each of the three issues listed above through the contributions of empirical, computational, and neuropsychological approaches.

Methods for implicit learning

How can we establish that knowledge is implicit?

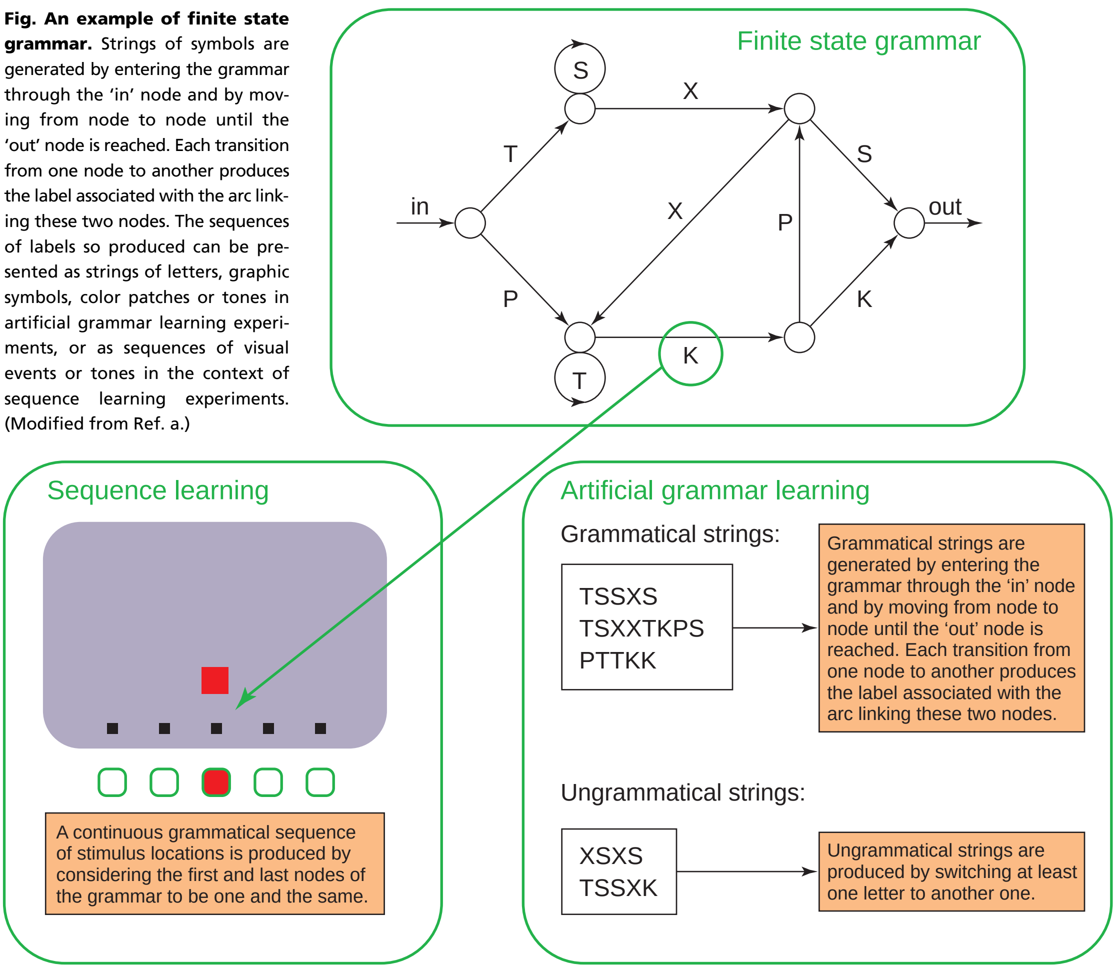
The most important conceptual problem in IL research is probably that, in the absence of any clear operational definition of awareness, learning can be described as implicit in several different ways according to whether one focuses on the *acquisition* processes, on the *knowledge* resulting from these processes, or on the *retrieval* processes[11]. While most definitions have emphasized the properties of both the learning processes and of the resulting knowledge, most of the empirical research has focused on establishing the extent to which the knowledge resulting from an IL episode can be characterized as unconscious.

However, the difficulty involved in demonstrating the existence of unconscious knowledge through dissociations between performance on different tasks has fostered other approaches, focused on attempting to establish functional dissociations between implicit and explicit learning by manipulating factors such as intention to learn or the availability of attentional resources during learning (e.g. by means of a secondary task). These functional approaches, which we review in the next section, raise the issue of whether IL should be characterized as a distinct mode of learning that relies on separable memory and processing systems.

Dissociation studies

As described in Box 2, most IL studies have taken the form of dissociation paradigms based on the rationale that to demonstrate IL, it is sufficient to demonstrate that performance on some learned task exceeds subject's awareness of the acquired knowledge. Various measures have been proposed to measure awareness: verbal reports, forced-choice tests (e.g.

Fig. An example of finite state grammar. Strings of symbols are generated by entering the grammar through the 'in' node and by moving from node to node until the 'out' node is reached. Each transition from one node to another produces the label associated with the arc linking these two nodes. The sequences of labels so produced can be presented as strings of letters, graphic symbols, color patches or tones in artificial grammar learning experiments, or as sequences of visual events or tones in the context of sequence learning experiments. (Modified from Ref. a.)



recognition) or subjective tests (e.g. confidence ratings). We review essential findings obtained using each test below.

Verbal reports

Subjects in IL experiments are consistently able to use knowledge that they cannot describe verbally and often express surprise when told that the material contains structure (see Box 2). Reber's original findings with the AGL paradigm were confirmed by more systematic experiments in which the content of subjects' reports was used to instruct naïve subjects[29] or to simulate classification performance[30]. The performance of naïve or simulated subjects was above chance but always below the classification level of experimental subjects, thus suggesting that the original reports failed to contain all of the relevant knowledge. Comparable results were found with both DSC tasks[3] and SL tasks[14,31–34].

Should such dissociations be interpreted as evidence for the existence of unconscious mechanisms of learning, however? Shanks and St John[6] have pointed out that tests of awareness should tap into the exact same knowledge upon which performance is based (the *information* criterion) and that they must be sensitive to all of the relevant conscious knowledge (the *sensitivity* criterion). By this account, verbal reports fail both criteria. Subjects might fail to report verbally knowledge held with low confidence, for instance. Worse, verbal reports could probe subjects about knowledge that they do not even need in order to perform the task. For instance, it is now clear that above-chance classification performance in AGL tasks does not require the rules of the underlying grammar (see Box 2 Fig.) to be known, but might instead be based on explicit knowledge of specific instances or chunks of the training strings[24,25,35]. Finding that subjects fail to report knowledge of rules in verbal reports is therefore expected rather than surprising. Several authors[33,34,36–38] have thus suggested that valid tests of awareness should involve forced-choice tests such as recognition.

Forced-choice tests

In the AGL paradigm, forced-choice tests have often taken the form of old/new recognition judgments on fragments of letter strings. In a significant study, Dulany *et al.*[39] asked subjects performing the AGL classification task to underline which letters they thought made the string grammatical or not, and found that these ratings correlated highly with subjects' classification performance, thus suggesting that subjects were in fact conscious of their knowledge. Other studies using old/new recognition judgments[25] or fragment completion tasks[30] have consistently shown that subjects' performance on objective tests is highly correlated with their grammaticality judgments. Similar results were obtained in SL experiments using measures such as recognition of sequence fragments[40,41] cued generation tasks (which require subjects to predict the next element of a sequence[15,34,42])

Box 3. Methods for implicit learning

How can we assess awareness in implicit learning studies? Objective tasks have often been taken to be process-pure measures of explicit knowledge. It is much more plausible, however, to conceptualize tasks in general as sensitive to both implicit and explicit influences. Hence, just as classification in an AGL task should not be taken as a pure measure of implicit influences, recognition can likewise not be safely assumed to constitute an exclusive and exhaustive index of conscious knowledge. This difficult 'contamination' problem has also arisen in fields such as implicit memory and subliminal perception. Different frameworks have been proposed to overcome it. These methods share the rationale of linking awareness with controlled responding. They involve comparing performance on tasks that differ only in whether subjects are specifically instructed to respond based on conscious knowledge vs. instructed to respond against this knowledge, or simply not given any specific instructions concerning the use of conscious knowledge.

Comparisons between direct and indirect tasks

Reingold and Merikle[a,b] have proposed to compare the relative sensitivity of direct and indirect tasks to conscious and unconscious influences. Tasks are matched in all characteristics, such as context and demands, except instructions. In direct tasks, subjects are explicitly instructed to respond based on conscious, task-relevant knowledge. In indirect tasks, the instructions make no reference to the relevant discriminations. The only assumption required for comparisons to be valid is that the sensitivity of the direct task to conscious knowledge should be greater than or equal to the sensitivity of the indirect task. If subjects show greater sensitivity to some features of the material in the indirect task vs. the direct task, one can conclude that this advantage is due to unconscious knowledge. Jiménez, Méndez and Cleeremans[c] applied this framework to sequence learning and showed that some knowledge about the sequential structure of the material was exclusively expressed in the indirect task (choice reaction time) and not in a comparable direct task (cued generation) – a result that suggests that this knowledge was unconscious.

The Process Dissociation Procedure

Jacoby[d] proposed the Process Dissociation Procedure (PDP) as a method to derive separate estimates of conscious (C) and unconscious (U) influences on memory. In a memory tasks for instance, the number of word stems completed with previously studied words is compared in two conditions: the 'inclusion' condition, in which subjects are asked to use studied words to complete the stems or, failing recollection, the first word that comes to mind, and the 'exclusion' condition, in which subjects are asked to exclude studied words. Jacoby described how different estimates of C and U influences can be derived from a comparison between these two conditions.

Buchner *et al.*[e,f] have adapted this framework to sequence learning, and showed: (1) that intention to learn increases C but leaves U unaffected; and (2) that explicit knowledge of the sequence influences performance early in training, while extended training is needed to detect implicit influence. In artificial grammar learning, Dienes *et al.*[g] found that subjects trained on two grammars had intentional control over which grammar to use during test, albeit they were also able to classify novel letter strings above chance despite believing they were guessing.

References

a Reingold, E.M. and Merikle, P.M. (1988) Using direct and indirect measures to study perception without awareness *Percept. Psychophys.* 44, 563–575

b Merikle, P.M. and Reingold, E.M. (1991) Comparing direct (explicit) and indirect (implicit) measures to study unconscious memory *J. Exp. Psychol. Learn. Mem. Cognit.* 17, 224–233

c Jiménez, L., Méndez, C. and Cleeremans, A. (1996) Comparing direct and indirect measures of sequences learning *J. Exp. Psychol. Learn. Mem. Cognit.* 22, 948–969

d Jacoby, L.L. (1991) A process dissociation framework: separating automatic from intentional uses of memory *J. Mem. Lang.* 30, 513–541

e Buchner, A. *et al.* (1997) A multinomial model to assess fluency and recollection in a sequence learning task *Q. J. Exp. Psychol.* 50, 631–663

f Buchner, A., Steffens, M.C. and Rothkegel, R. (1998) On the role of fragmentary knowledge in a sequence learning task *Q. J. Exp. Psychol.* 51, 251–281

g Dienes, Z. *et al.* (1995) Unconscious knowledge of artificial grammars is applied strategically *J. Exp. Psychol. Learn. Mem. Cognit.* 21, 1322–1338

or free generation[40] as measures of explicit knowledge. With a few exceptions[34,38] that turned out not to be immune from methodological criticism, all of these studies have indicated that subjects are consistently able to express part of the knowledge they have acquired during training in subsequent forced-choice measures.

While such results prompted many critics of IL to conclude that there is in fact no evidence for implicit knowledge[6,40], other authors have questioned the dissociation strategy itself based on the argument that it unrealistically requires the test of awareness to be absolute, that is, to be simultaneously sensitive to *all* of a subject's conscious knowledge (exhaustiveness) and *only* to the relevant conscious knowledge (exclusiveness). Similar issues raised in the implicit memory and subliminal perception literatures have fostered the development of new methodologies (see Box 3) that take it as a starting point that tasks in general are not process-pure, and that have now started to be applied to IL situations.

Subjective tests

Dienes and Berry[3] have suggested to use a subjective rather than objective criterion to distinguish implicit from explicit learning[19]. According to this framework, learning is implicit when subjects who perform above chance in a direct test lack metaknowledge, either because they believe they are guessing (the *guessing* criterion) or because their accuracy is unrelated to their confidence judgments (the *zero-correlation* criterion). So far, only a few studies have used a subjective criterion. In AGL experiments, subjects asked to produce confidence ratings when classifying strings as grammatical or not[43,44] exhibited above-chance performance while believing they were guessing. A similar result was obtained in SL through a generation task[45].

To summarize, it appears that the claim for IL very much depends on the specific criterion one has chosen to assess awareness. While it is clear that IL might occur when awareness is assessed through verbal reports or through subjective criteria, the current evidence from assessment through

Box 4. The neural bases of implicit learning

Special populations, in particular amnesic patients, are particularly relevant to the study of implicit learning because the functional deficits they exhibit offer the promise of rooting dissociation findings in neuroanatomical evidence. Likewise, neuroimaging studies can usefully inform IL research by showing directly which brain areas are specifically involved under different tasks or instructional set, thus potentially overcoming the difficult problem of making inferences about the nature of learning based only on the outcome of such learning. We here briefly review the contributions of each approach.

Neuropsychological studies of implicit learning

Densely amnesic patients exhibit near-normal performance in both artificial grammar learning[a–c] and sequence learning tasks[d,e] despite specific deficits on direct tests such as recognition or cued prediction respectively. While such findings have been taken as suggestive evidence that separable memory systems are involved in implicit and explicit learning and memory, the studies that have been conducted to date have also been questioned[f,g] based on methodological concerns. Hence, while the study of amnesic patients is undoubtedly one of the more interesting avenues of research through which to explore implicit learning, it appears premature to conclude that the research conducted to date offers strong support for the notion that separate memory and processing systems subserve implicit learning.

Neuroimaging studies of implicit learning

Brain imaging techniques such as event-related brain potentials (ERP), functional magnetic resonance imaging (fMRI) or positron emission tomography (PET) have recently been applied to sequence learning[h]. In general, such studies are suggestive that distinct networks might be involved depending on whether subjects are aware or not of the material they learn[i,j] and generally seem to support the ideas: (1) that learning directly produces changes in the brain areas involved in performance; and (2) that additional distinct areas are involved when subjects report awareness. One recent study[k] has reported the intriguing finding that some brain areas might be responsive to novelty in the absence of awareness.

References

a Knowlton, B.J., Ramus, S.J. and Squire, L.R. (1992) Intact artificial grammar learning in amnesia: dissociation of classification learning and explicit memory for specific instances *Psychol. Sci.* 3, 172–179

b Knowlton, B.J. and Squire, L.R. (1994) The information acquired during artificial grammar learning *J. Exp. Psychol. Learn. Mem. Cognit.* 20, 79–91

c Knowlton, B.J. and Squire, L.R. (1996) Artificial grammar learning depends on implicit acquisition of both abstract and exemplar-specific information *J. Exp. Psychol. Learn. Mem. Cognit.* 22, 169–181

d Nissen, M.J. and Bullemer, P. (1987) Attentional requirement of learning: Evidence from performance measures *Cognit. Psychol.* 19, 1–32

e Reber, P.J. and Squire, L.R. (1994) Parallel brain systems for learning with and without awareness *Learn. Mem.* 1, 217–229

f Shanks, D.R. and Johnstone, T. (1998) Implicit knowledge in sequential learning tasks, in *Handbook of Implicit Learning* (Stadler, M.A. and Frensch, P.A., eds), pp. 533–572, Sage Publications

g Curran, T. (1998) Implicit sequence learning from a cognitive neuroscience perspective: what, how, and where?, in *Handbook of Implicit Learning* (Stadler, M.A. and Frensch, P.A., eds), pp. 365–400, Sage Publications

h Clegg, B.J., DiGirolamo, J. and Keele, S.W. (1998) A review of sequence learning *Trends Cognit. Sci.* 2, 275–281

i Raush, S.L. *et al.* (1995) A PET investigation of implicit and explicit sequence learning *Hum. Brain Mapp.* 3, 271–286

j Hazeltine, E., Grafton, S.T. and Ivry, R. (1997) Attention and stimulus characteristics determine the locus of motor sequence encoding: a PET study *Brain* 120, 123–140

k Berns, G.S., Cohen, J.D. and Mintun, M.A. (1997) Brain regions responsive to novelty in the absence of awareness *Science* 276, 1272–1275

objective criteria is inconclusive. This is partly because the extent to which such tests constitute exclusive measures of awareness can be questioned, and partly because alternative methods (Box 3) have not yet been widely used.

Functional approaches of implicit learning

What is implicit about implicit learning? Are there multiple systems involved in implicit learning?

Given the difficulty of assessing awareness discussed in the previous section, other approaches to IL have focused on the nature of the processes engaged in IL tasks rather than on the nature of the acquired knowledge. Such approaches have tended to consider IL to be best described as an automatic learning process that occurs without intention, regardless of the status of the resulting knowledge with respect to the conscious/unconscious dimension[4,46,47], and have focused on exploring the influence of variables such as intention to learn, attention, stimulus complexity, and task demands on both task performance and measures of awareness.

Orientation to learn

Intention to learn can be manipulated by asking 'intentional' subjects to attempt to discover the rules, or by providing them with detailed information about the structure contained in the stimulus material, while providing 'incidental' subjects with neutral instructions that do not refer to the existence of regularities. In the SL paradigm, Frensch and Miner[48] showed that intentional subjects performed better than incidental subjects in a SL task involving a simple repeating pattern. However, this advantage disappears when the sequence is probabilistic[36], thus suggesting that orientation to learn interacts with stimulus complexity. Similar effects and interactions with stimulus salience were reported in the context of AGL situations[49]. Hence looking for rules helps, but only if rules can be found, that is, only when the regularities contained in the material are sufficiently salient. In DSC tasks, explanations about the workings of the simulated system improve subject's ability to answer questions about it but not their ability to control it[13].

Attention

Other studies have extensively explored the dependence of IL on attentional resources. If IL involves automatic processes that engage independent systems, it should be possible to obtain learning even in conditions where attention is otherwise engaged. Many studies have explored the

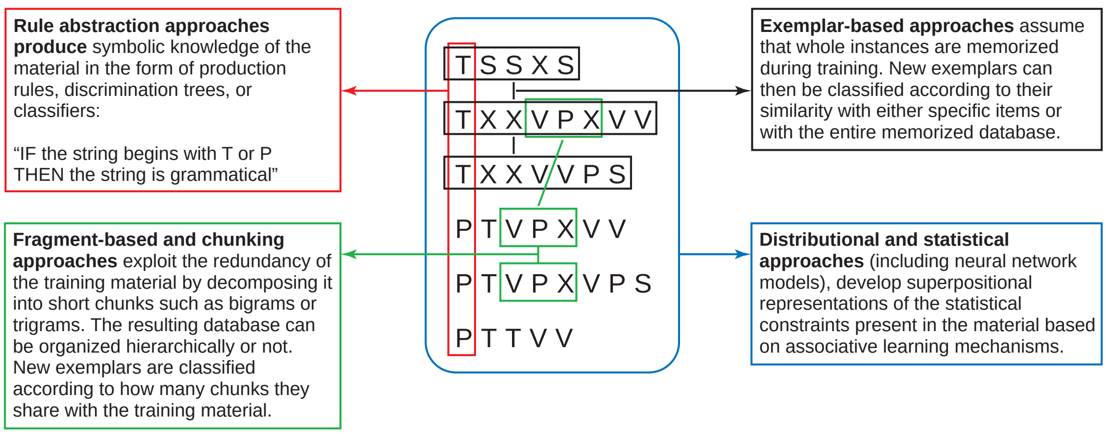


Fig. 1 An illustration of different computational approaches to artificial grammar learning. Each approach makes different assumptions about the processes and knowledge representations involved in memorizing a set of letter strings generated from a finite-state grammar. The same approaches are also relevant to sequence learning paradigms if the strings are taken to be continuous sequences of visual events.

effects of secondary tasks on performance, particularly in the context of SL situations[38,50–53]. Typically, the secondary task requires subjects to keep a running count of tones presented between the trials of the SRT task. In such conditions, it has generally been observed that learning still takes place, but is often significantly impaired. Further, availability of attentional resources also interacts with both stimulus complexity[54,55], and with orientation to learn: Subjects asked to memorize the sequence before training in SL tasks exhibit large savings compared with uninformed subjects, but only when the reaction time task is performed under conditions of undivided attention[56]. Similar findings using a random number generation secondary task were reported in both AGL[30,43] and DSC studies[57]. Overall, it appears that IL occurs under divided attention, but to a lesser extent so than when attention is fully available.

Multiple systems

While some authors have considered that preserved IL under dual-task conditions is evidence for an independent learning system[50,56], further research has suggested otherwise, based on the possibility that dual tasks such a tone-counting interfere not with the availability of attentional resources per se, but with the usability of explicit knowledge[23] or with the temporal organization of the sequence[53]. One can also question whether the secondary task fully exhausts mental capacity. Finally, it is important to note that attention is itself an ill-defined concept that refers to both 'mental capacity' and to 'selection'. A recent SL study[55] that manipulated these two factors separately found that: (1) IL only occurred when stimuli were task-relevant and attended to, but (2) that learning was unaffected by the presence of a secondary task. Simulation models have generally tended to suggest unitary accounts of the effects of attention[23,58].

Whether IL is subserved by independent memory and processing systems might be a difficult question to settle empirically. In this respect, recent neuropsychological evidence and neuroimaging techniques (Box 4) could offer significant new ways of approaching these issues.

In summary, the results based on functional approaches to IL suggest that it is relatively robust in the face of distraction and independent of subjects' orientation to learn. We believe that the results are consistent with the idea that IL processes occur in parallel with additional processes that are more dependent on the availability of explicit knowledge, on intention, and on attention, but the evidence is inconclusive regarding the extent and nature of interaction between these two kinds of processes.

Mechanisms for implicit learning

How is implicit knowledge acquired and represented?

Early characterizations of implicit knowledge have tended to describe it as 'abstract', based on findings that subjects exhibit better-than-chance transfer performance, as when asked to make grammaticality judgments on novel letter strings in the context of AGL situations[12,59,60]. Likewise, it has often been assumed that the reaction time savings observed in SL tasks reflect the acquisition of 'deep' knowledge about the rules used to generate the stimulus material[31,32]. These 'abstractionist' accounts have generally left it unspecified what the form of the acquired knowledge might be, short of noting that it must somehow represent the structure of the stimuli and their relationships, and be independent of the surface features of the material. The latter claim was further substantiated by findings that AGL knowledge transfers to strings based on the same grammar but instantiated with a different letter set[29,61], or even across modalities, as when training involves letter strings but transfer involves tone sequences[62].

However, there is considerable evidence that 'non-abstractionist' mechanisms are largely sufficient to account for the data. Brooks and colleagues[22,63,64] first suggested that subjects in AGL experiments were classifying novel strings based not on abstract knowledge of the rules, but simply based on the extent to which novel grammatical or ungrammatical strings are similar to 'whole exemplars' memorized during training. Perruchet and colleagues[25] showed that the knowledge acquired in both AGL and SL tasks might consist of little more than explicitly memorized short fragments

Box 5. Neural-network models of implicit learning

Neural-network models are particularly attractive as models of implicit learning because they involve continuously operating elementary associative learning processes and produce distributed knowledge represented in the very same structures that support processing. A number of architectures have been applied to all three main IL paradigms. Dienes[a] found that several versions of simple auto-associator networks trained to memorize AGL stimuli were able to classify new strings better than competing exemplar-based models. Gibson *et al.*[b] recently modeled performance in dynamic control task situations using the 'forward' models introduced by Jordan and Rumelhart[c].

In sequence learning, the most successful models are based on Elman's simple recurrent network (SRN), shown in the Figure. The SRN is a three-layer, back-propagation network that is typically assigned the task of predicting the next item in a sequence. This prediction task requires that the network be sensitive to the temporal context in which successive elements occur. The SRN develops such sensitivity by means of fixed one-to-one recurrent connections between the hidden units and a pool of context units, which, on each time-step through a sequence, contains a representation of the previous time step's hidden units activation vector. Over training, the network learns to base its predictions on an increasingly large and self-developed temporal window. The model has been successfully applied to numerous findings in sequence learning[d,e] as well as in artificial grammar learning situations (Ref. a and M. Redington, 1996, unpublished PhD thesis). In a particularly interesting extension to the model, Dienes[f] showed that it could be used to account for performance in artificial grammar learning tasks that involve transfer to strings composed of entirely new letters, thereby showing how such transfer could also be accounted without resorting to abstract, symbolic mechanisms. Other influential models relevant to sequence learning include Jordan's network[g] (see also Keele and Jennings[h]) and a model recently introduced by Dominey[i].

Finally, Mathis and Mozer[j] used a neural-network model to provide a computational account of consciousness. The model implements the idea that consciousness consists of stable representations, and assumes that the cognitive system consists of many interconnected modules each composed of a feedforward mapping network and of a constraint satisfaction network, the attractors of which correspond to well-formed entities of the domain. The mapping network determines the module's output to its inputs in a single time step, and also causes the attractor network to begin a relaxation process, at the end of which its activity will have settled in one of the attractors. When the input is only transient, as in typical subliminal priming studies[k] the attractor network fails to settle (and hence fails to produce conscious experience) for lack of sufficient input, but the mapping network can still influence the module's outputs.

References

a Dienes, Z. (1992) Connectionist and memory-array models of artificial grammar learning *Cognit. Sci.* 16, 41–79

b Gibson, F., Fichman, M. and Plaut, D.C. (1997) Learning in dynamic decision task: computational models and empirical evidence *Organization. Behav. Hum. Decis. Process.* 71, 1–35

c Jordan, M.I. and Rumelhart, D.E. (1992) Forward models: supervised learning with a distal teacher *Cognit. Sci.* 16, 307–354

d Cleeremans, A. and McClelland, J.L. (1991) Learning the structure of event sequences *J. Exp. Psychol. Gen.* 120, 235–253

e Cleeremans, A. (1993) *Mechanisms of Implicit Learning: Connectionist Models of Sequence*, MIT Press

f Dienes, Z., Altmann, G. and Gao, S-J. Mapping across domains without feedback: a neural-network model of implicit learning *Cognit. Sci.* (in press)

g Jordan, M.I. (1986) Attractor dynamics and parallelism in a connectionist sequential machine, in *Proceedings of the Eighth Annual Conference of the Cognitive Science Society*, pp. 531–546, Erlbaum

h Keele, S.W. and Jennings, P.J. (1992) Attention in the representation of sequence: experiment and theory *Hum. Mov. Sci.* 11, 125–138

i Dominey, P.F. (1998) Influences of temporal organization on sequence learning and transfer: comments on Stadler (1995) and Curran and Keele (1993) *J. Exp. Psychol. Learn. Mem. Cognit.* 24, 234–248

j Mathis, W.D. and Mozer, M.C. (1996) Conscious and unconscious perception: A computational theory, in *Proceedings of the Eighteenth Annual Conference of the Cognitive Science Society*, pp. 324–328, Erlbaum

k Marcel, T. (1980) Conscious and preconscious recognition of polysemous words: locating the selective effects of prior verbal context, in *Attention and Performance* (Nickerson, R.S., ed.), pp. 435–457, Erlbaum

l Elman, J.L. (1990) Finding structure in time *Cognit. Sci.* 14, 179–211

m Cleeremans, A. and Jiménez, L. (1998) Implicit sequence learning: the truth is in the details, in *Handbook of Implicit Learning* (Stadler, M.A. and Frensch, P.A., eds), pp. 323–364, Sage Publications

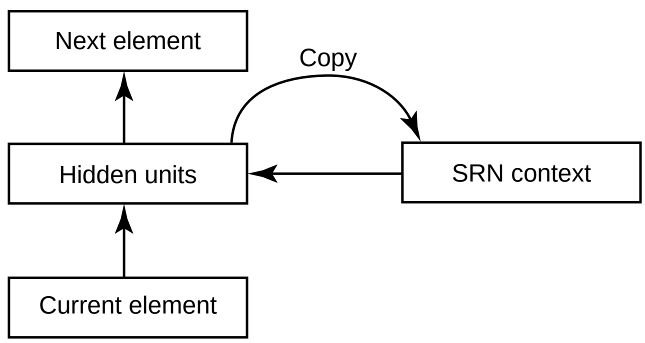


Fig. The simple-recurrent-network model. This has been applied both to artificial grammar learning and to sequence learning tasks[d]. (Modified from Refs l,m.)

or 'chunks' of the training material such as bigrams or trigrams, or simple frequency counts. Both learning and transfer performance can then be accounted for by the extent to which novel material contains memorized chunks. Figure 1 illustrates some of the possibilities that have been suggested in the context of AGL tasks, ranging from purely exemplar-based approaches to neural-network models.

More recently, hybrid accounts that assume separate memory systems for representing general or specific knowledge in AGL tasks have been proposed[65–67] based on evidence that significant sensitivity to grammaticality remains even when similarity and fragment overlap is carefully controlled for.

Overall, while it is clear that the knowledge acquired in typical IL situations need not be based on the unconscious acquisition of symbolic rules, significant areas of debate remain about the extent to which unitary, fragment-based mechanisms are sufficient to account for sensitivity to both the general and specific features of the training material. Simulation models, however (see below) have generally been suggestive that such mechanisms are in fact sufficient to account simultaneously for both grammaticality and similarity effects.

The role of computational modeling

Detailed computational models have now been proposed for all three main paradigms of IL (Refs 23,35,43,68,69). Two families of models are currently most influential: neural-network models (see Box 5), and fragment-based models based on Servan-Schreiber and Anderson's

Outstanding questions

- What are the limits of implicit learning? How complex can the stimulus material be?
- What is the role of consciousness in cognition?
- How does implicit learning relate to subliminal perception and implicit memory?
- Are there separate brain systems involved in implicit learning?
- To what extent does implicit learning depend on working memory and on attention?
- What is the role of implicit learning in cognitive development?

Competitive Chunking model[35], which, like other fragment-based approaches[4], assumes a continuous process of chunk creation and application. While no model can currently claim generality, both approaches share a number of central properties:

- Learning involves elementary association or recoding processes that are highly sensitive to the statistical features of the training set.
- Learning is incremental, continuous, and best characterized as a by-product of ongoing processing.
- Learning is based on the processing of exemplars and produces distributed knowledge.
- Learning is unsupervised and self-organizing.

Based on these properties of successful models of IL, it is appealing to consider it as a complex form of priming whereby experience continuously shapes memory, and through which stored traces in turn continuously influence further processing. Such priming, far from involving the sort of passive and automatic acquisition of abstract structure that were previously assumed to lie at the heart of IL, is in fact highly dependent on task demands during acquisition and on the congruence between learning and transfer conditions, as several recent studies have indicated[70,71].

Finally, while both fragment-based and neural-network models make it clear how sensitivity to the distributional properties of an ensemble of stimuli can emerge out of the processing of exemplars, they differ in whether they assume that the shared features of the training materials are represented as such or merely computed when needed. This 'locus of abstraction' issue is a difficult one that is unlikely to be resolved by modeling alone[72].

Thus, overall, it appears that the knowledge acquired in all three IL paradigms is best described as lying somewhere on a continuum between purely exemplar-based representations and more general, abstract representations – a characteristic that neural-network models are particularly apt at capturing.

Conclusions

Implicit learning is a fundamental and ubiquitous process in cognition. After decades of surprisingly scarce theoretical development about IL, several integrative proposals have been formulated over the past few years[3,15,28,60,70,73,74]. These integrative frameworks offer sharply contrasted perspectives on the role of consciousness in cognition, and reflect a field that remains significantly divided. While our review of the domain suggests that current debates about the defining features of implicit learning are likely to continue, there are also grounds to be confident that converging advances on several fronts hold the promise of resolving today's controversies. In particular, the field should benefit from: (1) a better understanding of the nature of consciousness; (2) increasing sophistication in the empirical methods used to explore IL; (3) further computational modeling aimed directly at addressing differences between corresponding direct and indirect tasks; and (4) functional brain imaging techniques and neuropsychological data. Overall, we believe that the available evidence suggests that IL is best characterized as a complex form of priming such that distributional knowledge acquired through incidental experience with a stimulus domain can influence processing in the absence of awareness that this knowledge was acquired or that it is currently influencing processing. In information-processing terms, implicit learning involves changes to the functional architecture of continuously learning systems such as neural networks[75]. Finally, from our perspective, while it appears that awareness usually accompanies learning and might often enhance it, it remains uncertain whether awareness is always necessary for learning to occur.

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References

1 Berry, D.C. (1997) *How Implicit is Implicit Learning?*, Oxford University Press

2 Cleeremans, A. and Content, A., eds (1997) Current directions in implicit learning (Special issue) *Psychologica Belgica* 37, 1–131

3 Dienes, Z. and Berry, D.C. (1997) Implicit learning: below the subjective threshold *Psychonomic Bull. Rev.* 4, 3–23

4 Perruchet, P., Vinter, A. and Gallego, J. (1997) Implicit learning shapes new conscious percepts and representations *Psychonomic Bull. Rev.* 4, 43–48

5 Seger, C.A. (1994) Implicit Learning *Psychol. Bull.* 115, 163–196

6 Shanks, D.R. and St John, M.F. (1994) Characteristics of dissociable human learning systems *Behav. Brain Sci.* 17, 367–447

7 Stadler, M.A. and Frensch, P.A. (1998) *Handbook of Implicit Learning*, Sage Publications

8 Whittlesea, B.W.A. and Dorken, M.D. (1997) Implicit learning: indirect, not unconscious *Psychonomic Bull. Rev.* 4, 63–67

9 Berry, D.C. and Dienes, Z. (1993) *Implicit Learning: Theoretical and Empirical Issues*, Erlbaum

10 Nisbett, R.E. and Wilson, T.D. (1977) Telling more than we can do: verbal reports on mental processes *Psychol. Rev.* 84, 231–259

11 Frensch, P.A. (1998) One concept, multiple meanings: on how to define the concept of implicit learning, in *Handbook of Implicit Learning* (Stadler, M.A. and Frensch, P.A., eds.), pp. 47–104, Sage Publications

12 Reber, A.S. (1967) Implicit learning of artificial grammars *J. Verbal Learn. Verbal Behav.* 6, 855–863

13 Berry, D.C. and Broadbent, D.E. (1984) On the relationship between task performance and associated verbalizable knowledge *Q. J. Exp. Psychol.* 39, 585–609

14 Nissen, M.J. and Bullemer, P. (1987) Attentional requirement of learning: evidence from performance measures *Cognit. Psychol.* 19, 1–32

15 Shanks, D.R., Green, R.E.A. and Kolodny, J.A. (1994) A critical examination of the evidence for unconscious (implicit) learning, in

Attention and Performance (Vol. 15) (Umiltà, C. and Moscovitch, M., eds), pp. 837–860, MIT Press

16 Bright, J.E.H. and Burton, A.M. (1994) Past midnight: semantic processing in an implicit learning task *Q. J. Exp. Psychol. Ser. A* 47, 71–89

17 Ellis, H.D., Ellis, D.M. and Hosie, J.A. (1993) Priming effects in children's face recognition *Br. J. Psychol.* 84, 101–110

18 Michas, I. and Berry, D.C. (1994) Implicit and explicit processes in a second language learning task *Eur. J. Cognit. Psychol.* 6, 357–381

19 Cheesman, J. and Merikle, P.M. (1984) Priming with and without awareness *Percept. Psychophys.* 36, 387–395

20 Schacter, D.L. (1987) Implicit memory: history and current status *J. Exp. Psychol. Learn. Mem. Cognit.* 13, 501–518

21 Loftus, E.F. and Klinger, M.R. (1992) Is the unconscious smart or dumb? *Am. Psychol.* 47, 761–765

22 Brooks, L.R. (1978) Non-analytic concept formation and memory for instances, in *Cognition and Concepts* (Rosch, E. and Lloyd, B., eds), pp. 16–211, Erlbaum

23 Cleeremans, A. (1993) *Mechanisms of Implicit Learning: Connectionist Models of Sequence Processing*, MIT Press

24 Perruchet, P., Gallego, J. and Savy, I. (1990) A critical reappraisal of the evidence for unconscious abstraction of deterministic rules in complex experimental situations *Cognit. Psychol.* 22, 493–516

25 Perruchet, P. and Pacteau, C. (1990) Synthetic grammar learning: implicit rule abstraction or explicit fragmentary knowledge? *J. Exp. Psychol. Gen.* 119, 264–275

26 Redington, M. and Chater, N. (1996) Transfer in artificial grammar learning: a reevaluation *J. Exp. Psychol. Gen.* 125, 123–138

27 Neal, A. and Hesketh, B. (1997) Episodic knowledge and implicit learning *Psychonomic Bull. Rev.* 4, 24–37

28 Perruchet, P. and Vinter, A. (1998) Learning and development: the implicit knowledge assumption reconsidered, in *Handbook of Implicit Learning* (Stadler, M.A. and Frensch, P.A., eds), pp. 495–531, Sage Publications

29 Mathews, R.C. *et al.* (1989) Role of implicit and explicit process in learning from examples: a synergistic effect *J. Exp. Psychol. Learn. Mem. Cognit.* 15, 1083–1100

30 Dienes, Z., Broadbent, D.E. and Berry, D.C. (1991) Implicit and explicit knowledge bases in artificial grammar learning *J. Exp. Psychol. Learn. Mem. Cognit.* 17, 875–887

31 Lewicki, P., Czysewska, M. and Hoffman, H. (1987) Unconscious acquisition of complex procedural knowledge *J. Exp. Psychol. Learn. Mem. Cognit.* 13, 523–530

32 Lewicki, P., Hill, T. and Bizot, E. (1988) Acquisition of procedural knowledge about a pattern of stimuli that cannot be articulated *Cognit. Psychol.* 20, 24–37

33 Stadler, M.A. (1989) On learning complex procedural knowledge *J. Exp. Psychol. Learn. Mem. Cognit.* 15, 1061–1069

34 Willingham, D.B., Nissen, M.J. and Bullemer, P. (1989) On the development of procedural knowledge *J. Exp. Psychol. Learn. Mem. Cognit.* 15, 1047–1060

35 Servan-Schreiber, E. and Anderson, J.R. (1990) Learning artificial grammar with competitive chunking *J. Exp. Psychol. Learn. Mem. Cognit.* 16, 592–608

36 Jiménez, L., Méndez, C. and Cleeremans, A. (1996) Comparing direct and indirect measures of sequences learning *J. Exp. Psychol. Learn. Mem. Cognit.* 22, 948–969

37 Jiménez, L. (1997) Implicit learning: conceptual and methodological issues *Psychologica Belgica* 37, 9–28

38 Reed, J. and Johnson, P. (1994) Assessing implicit learning with indirect tests: determining what is learned about sequence structure *J. Exp. Psychol. Learn. Mem. Cognit.* 20, 585–594

39 Dulany, D.E., Carlson, R.A. and Dewey, G.I. (1984) A case of syntactical learning and judgment: how conscious and how abstract? *J. Exp. Psychol. Gen.* 113, 541–555

40 Perruchet, P. and Amorim, M.A. (1992) Conscious knowledge and changes in performance in sequence learning: evidence against dissociation *J. Exp. Psychol. Learn. Mem. Cognit.* 18, 785–800

41 Willingham, D.B., Greeley, T. and Bardone, A.M. (1993) Dissociation in a serial response time task using a recognition measure: comment on Perruchet and Amorim (1992) *J. Exp. Psychol. Learn. Mem. Cognit.* 19, 1424–1430

42 Cleeremans, A. and McClelland, J.L. (1991) Learning the structure of event sequences *J. Exp. Psychol. Gen.* 120, 235–253

43 Dienes, Z. *et al.* (1995) Unconscious knowledge of artificial grammars is applied strategically *J. Exp. Psychol. Learn. Mem. Cognit.* 21, 1322–1338

44 Dienes, Z. and Altmann, G.T.M. (1997) Transfer of implicit knowledge across domains: how implicit and how abstract?, in *How Implicit is Implicit Learning?* (Berry, D.C., ed.), pp. 107–123, Oxford University Press

45 Shanks, D.R. and Johnstone, T. (1998) Implicit knowledge in sequential learning tasks, in *Handbook of Implicit Learning* (Stadler, M.A. and Frensch, P.A., eds), pp. 533–572, Sage Publications

46 Mathews, R.C. and Roussel, L.G. (1997) Abstractness of implicit knowledge: a cognitive evolutionary perspective, in *How Implicit is Implicit Learning?* (Berry, D.C., ed.), pp. 13–47, Oxford University Press

47 Stadler, M.A. and Frensch, P.A. (1994) Wither learning, wither memory? *Behav. Brain Sci.* 17, 423–424

48 Frensch, P.A. and Miner, C.S. (1994) Effects of presentation rate and individual difference in short-term memory *Mem. Cognit.* 22, 95–110

49 Reber, A.S. and Lewis, S. (1977) Implicit learning: an analysis of the form and structure of a body of tacit knowledge *Cognition* 114, 14–24

50 Cohen, A., Ivry, R.I. and Keele, S.W. (1990) Attention and structure in sequence learning *J. Exp. Psychol. Learn. Mem. Cognit.* 16, 17–30

51 Shanks, D.R., Johnstone, T. and Staggs, L. (1997) Abstraction processes in artificial grammar learning *Q. J. Exp. Psychol.* 50, 216–252

52 Frensch, P.A., Buchner, A. and Lin, J. (1994) Implicit learning of unique and ambiguous serial transitions in the presence and absence of a distractor task *J. Exp. Psychol. Learn. Mem. Cognit.* 20, 567–584

53 Stadler, M.A. (1995) Role of attention in implicit learning *J. Exp. Psychol. Learn. Mem. Cognit.* 21, 674–685

54 Cleeremans, A. and Jiménez, L. (1998) Implicit sequence learning: the truth is in the details, in *Handbook of Implicit Learning* (Stadler, M.A. and Frensch, P.A., eds), pp. 323–364, Sage Publications

55 Jiménez, L. and Méndez, C. Which attention is needed for implicit learning? *J. Exp. Psychol. Learn. Mem. Cognit.* (in press)

56 Curran, T. and Keele, S.W. (1993) Attentional and nonattentional forms of sequence learning *J. Exp. Psychol. Learn. Mem. Cognit.* 19, 189–202

57 Hayes, N. and Broadbent, D.E. (1988) Two modes of learning for interactive tasks *Cognition* 28, 249–276

58 Dominey, P.F. (1998) Influences of temporal organization on sequence learning and transfer: comments on Stadler (1995) and Curran and Keele (1993) *J. Exp. Psychol. Learn. Mem. Cognit.* 24, 234–248

59 Reber, A.S. (1989) Implicit learning and tacit knowledge *J. Exp. Psychol. Gen.* 118, 219–235

60 Reber, A.S. (1993) *Implicit Learning and Tacit Knowledge: An Essay on the Cognitive Unconscious*, Oxford University Press

61 Reber, A.S. (1969) Transfer of syntactic structure in synthetic languages *J. Exp. Psychol.* 81, 115–119

62 Altmann, G.T.M., Dienes, Z. and Goode, A. (1995) Modality independence of implicitly learned grammatical knowledge *J. Exp. Psychol. Learn. Mem. Cognit.* 21, 899–912

63 Brooks, L.R. and Vokey, J.R. (1991) Abstract analogies and abstracted grammars: comments on Reber (1989) and Mathews *et al.* (1989) *J. Exp. Psychol. Gen.* 120, 316–323

64 Vokey, J.R. and Brooks, L.R. (1992) Salience of item knowledge in learning artificial grammar *J. Exp. Psychol. Learn. Mem. Cognit.* 18, 328–344

65 Knowlton, B.J. and Squire, L.R. (1994) The information acquired during artificial grammar learning *J. Exp. Psychol. Learn. Mem. Cognit.* 20, 79–91

66 Knowlton, B.J. and Squire, L.R. (1996) Artificial grammar learning depends on implicit acquisition of both abstract and exemplar-specific information *J. Exp. Psychol. Learn. Mem. Cognit.* 22, 169–181

67 Meulemans, T. and Van Der Linden, M. (1997) Associative chunk strength in artificial grammar learning *J. Exp. Psychol. Learn. Mem. Cognit.* 23, 1007–1028

68 Gibson, F., Fichman, M. and Plaut, D.C. (1997) Learning in dynamic decision task: computational models and empirical evidence *Org. Behav. Hum. Decis. Process.* 71, 1–35

69 Dienes, Z. (1992) Connectionist and memory-array models of artificial grammar learning *Cognit. Sci.* 16, 41–79

70 Whittlesea, B.W.A. and Dorken, M.D. (1993) Incidentally, things in general are particularly determined: an episodic-processing account of implicit learning *J. Exp. Psychol. Gen.* 122, 227–248

71 Whittlesea, B.W.A. and Wright, R. (1997) Implicit (and explicit) learning: acting adaptively without knowing the consequences *J. Exp. Psychol. Learn. Mem. Cognit.* 23, 181–200

72 Barsalou, L.W. (1990) On the indistinguishability of examplar memory and abstraction in category representation, in *Content and Process Specificity in the Effects on Prior Experiences* (Srull, T.K. and Wyer, R.S., eds), pp. 61–88, Erlbaum

73 Cleeremans, A. (1997) Principles for implicit learning, in *How Implicit is Implicit Learning?* (Berry, D.C., ed.), pp. 195–234, Oxford University Press

74 Dulany, D.E. (1997) Consciousness in the explicit (deliberative) and implicit (evocative), in *Scientific Approaches to Consciousness* (Cohen, J.D. and Schooler, J.W., eds), pp. 179–212, Erlbaum

75 Becker, S. *et al.* (1997) Long-term semantic priming: a computational account and empirical evidence *J. Exp. Psychol. Learn. Mem. Cognit.* 23, 1059–1082

Mind as Action

by James V. Wertsch, Oxford University Press, 1998. £22.95 (xii + 203 pages)
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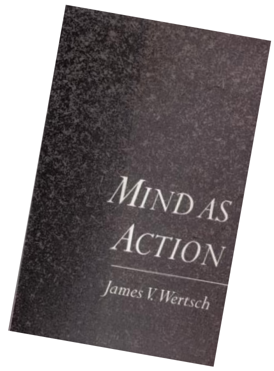

Mind as Action is the latest refinement of Wertsch's theory of socially mediated mind[1,2]. With his usual clear prose and effective balance of theory and experimental evidence, Wertsch argues that neither social nor biological reductionism is the proper methodological stance (Chapter 1), since both lead to essentialism (for a similar, more detailed argument, see Chapters 1 and 2 in Ref. 3). The unit of psychological study is 'mediated action' – the agent and sociohistorical means in mutual determination – a proposal that directly takes on the often-defaulted promissory note in cultural psychology of a unit of analysis that can be identified by someone other than the believer.

Wertsch follows through with an important catalogue of properties of mediated action (Chapter 2), the use of which can lead sociocultural research programs in new directions. For example, mediation constrains as much as it facilitates, and so even well-intentioned mediational contexts can restrict inquiry by reproducing their limiting conditions while claiming otherwise. Moreover, mediation can be accidental, with some sociocultural affordances the inadvertent consequence of other cultural means. I take this as evidence that culture is both sub-optimal and open (with contextual mind operating as a kind of social exaptation[4] or characteristic that arose in a way unrelated to its present function; for a good discussion of how social facts originate and change semiotic function, see Ref. 5). Importantly, this view yields leeway for individual action and productive error in the development of mediated mind.

One of the most powerful and prevalent cultural mediations of mental action is narrative. Wertsch describes how this form of discourse both facilitates and limits access to historical knowledge in schools (Chapter 3). The linguistic structure of American students' historical narratives suggests that they move from a dispersed understanding of their own history in fragmented narrative form (fostered by textbooks that fail to promote the coherence of the historical story) to an overcoherent understanding guided by a quest-for-freedom narrative that excludes alternatives. The educational problem is how to engender coherence without exclusion.

This kind of analysis of emergent historical mind might be advanced in two ways. One is by using the work of Kieran Egan[6], who has identified five kinds of understanding that guide the development and instruction of historical knowledge – somatic, mythic, romantic, philosophic, and ironic. These might provide a framework for examining the student-produced historical narratives that drive Wertsch's analysis. For example, the quest-for-freedom narrative appears to be one at the transition between romantic knowing (literate, personal narrative) and philosophic knowing (abstract, truth-driven narrative); the satirical narratives of college students are clearly at the level of ironic knowing (self-critical meta-narrative); fifth- and eighth-grade narratives appear to be mythic knowing (oral, binarily structured narrative).

A second enhancement of Wertsch's narrative analysis might come from using the notion of 'illocutionary point': the ultimate pragmatic goal of speech action. When students, and official historians, produce narratives in which the constituent propositions are factually correct but which, together, make a text that is pragmatically skewed (as in the reporting of correct American settlement facts in the service of a dubious quest for freedom), then the consumers of such historical narratives must deploy elaborate inference chains to plug the gap between truth and appropriateness. It would be worthwhile studying the strategies of reasoning from text-based speech acts to try to locate the ways that illocutionary point in historical narratives is coded and used.

In looking at how linguistic mediation generally works in forming the educated mind (Chapter 4), Wertsch nicely shows how many school failures result from mismatches in speech genre[7] between the child and the school. The solution involves appropriation of the actual speech of school exchange in the service of a learner's self-regulation. The larger lesson, as I see it, is that educational progress comes from changing the participatory structure of educational intersubjectivity and from manipulating mediation in its material forms (actual speech) – in short, a change in the mediated action of schooling.

Lest this suggest a happily-ever-after scenario for schools, we should recall the lesson of Chapter 5: resistance and appropriation are two sides of the same coin. The narrative choices of school-based knowledge give voice to some ideas at the expense of others – either by quiet approval or by deliberate silencing. The more institutionalized the unvoiced narratives become, the more dialectical tension there will be in the mediated mental action of school. Can this tension between the said and the unsaid be a productive force in education?

I recall my three-and-a-half-year-old daughter working on a preschool book in which she had to identify all the things that 'belong together.' On one page, there was a picture of a boy, a girl, a school, and a clown. She put them all together, saying that the boy and girl belong in the school, and the clown does also because 'a clown is a people, too.' Think of the hard work needed to legitimate – that is, not exclude – that insight in her school performance, to use it as a way to push her knowledge forward, rather than to bracket it out as unspeakable in the official narrative of logic. Think especially of how the relationship between her and her teachers, her family, her classmates (i.e. she *and other people*) would all have to be involved for