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# IMPLICIT LEARNING AND SECOND LANGUAGE ACQUISITION

## A cognitive psychology perspective

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### Introduction

There are two distinct yet related research strands within cognitive psychology that are directly relevant to the study of how we learn a second language, namely *implicit learning* and *statistical learning* (see Textbox 23.1). The two strands prioritize different research themes and questions, and they rely on different experimental paradigms, as illustrated in the section "Implicit learning paradigms", below. Despite these differences, implicit learning and statistical learning studies share many commonalities, and there have been calls for closer alignment between the two lines of investigation (Rebuschat & Monaghan, 2019).

Second language research has much to gain from the theoretical insights and methodological advances developed in implicit learning and statistical learning research. Implicit learning has placed the cognitive unconscious back at the heart of research on language learning (Reber, 2022), and it has promoted experimental tasks and paradigms that allow us to distinguish the contributions of implicit and explicit processes in language learning. Statistical learning has demonstrated convincingly that infants and very young children can acquire different aspects of language by tracking statistical information in the input, thus providing an essential proof of concept for the potential role of implicit learning in language acquisition (Frost

**Textbox 23.1 Key terms and concepts**

Implicit learning: Deriving information from the environment without awareness of what was learned. Usually observed under incidental exposure conditions, i.e., when participants are not informed about the learning target and the surprise test.

Explicit learning: Deriving information from the environment by means of conscious learning strategies (e.g., hypothesis formation and testing). Usually associated with intentional exposure conditions, i.e., when participants are informed about the learning target and are actively trying to acquire it.

Statistical learning: Learning from the distributional properties of the environment. The process entails computations based on units or patterns (sounds, syllables, syntactic categories, etc.).



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et al., 2019). Implicit learning and statistical learning research contribute to our understanding of fundamental processes of (child and adult) language learning. In return, second language acquisition (SLA) research contributes an applied perspective that is frequently missing in implicit and statistical learning research.

## Experimental paradigms

In this section, we briefly review four paradigms that are widely used in implicit learning and statistical learning research. An introduction to these experimental tasks will provide us with a better understanding of the evidence base discussed in the following sections.

### *Implicit learning paradigms*

The experimental arrangements in implicit learning research generally have the following characteristics. Participants (usually adults) are trained under incidental exposure conditions, i.e., they are not informed of the learning target or of the subsequent test of learning. Experiments include a measure of learning (to determine what was acquired following exposure) and a measure of awareness (to determine if the acquired knowledge is conscious or not). The term *implicit* learning is usually reserved for those instances in which the awareness measure suggests the presence of at least some implicit (unconscious) knowledge. Otherwise, the term *incidental* learning is preferred (see Williams, 2009, for discussion). Finally, the learning target tends to be fairly complex. As Reber (1993) points out, implicit learning is more likely to be observed when the learning target is too challenging to acquire through explicit means (e.g., via hypothesis formation and testing). This type of arrangement can be found in two classic paradigms that have been used extensively in implicit learning research, namely artificial grammar learning (AGL) and sequence learning.

In the classic AGL procedure (Reber, 1967, Expt. 2), participants are first asked to memorize meaningless letter strings (e.g., TPPTS, VXXVPXVS) that—unbeknownst to them—were generated by a complex, artificial grammar. They are then given a surprise test (usually a grammaticality judgment task, GJT) to determine what aspects of the grammar they have learned. Participants also complete a measure of awareness to determine if the acquired knowledge is conscious or not. Traditionally, this has been done by prompting participants to report rules or patterns they might have noticed (retrospective verbal reports).

There are several types of sequence learning tasks. The best-known is the serial reaction time (SRT) task, developed by Nissen and Bullemer (1987). Here, participants observe a visual cue (e.g., an asterisk) that can appear in different locations (A-B-C-D) on the computer screen. Their task is to simply respond to the cue by pressing on a button associated with the cue as quickly and accurately as possible. Participants are not informed that, on the majority of trials, the location is determined by a repeating sequence (e.g., D-B-C-A-C-B-D-C-B-A). Learning is measured by comparing response times over runs of trials that do and do not follow the fixed sequence. Awareness is typically measured by asking participants to generate completions to sequences, or by recognition memory for fragments of the fixed versus random sequences.

### *Statistical learning paradigms*

Experimental arrangements in statistical learning research are characterized by the careful manipulation of input statistics, e.g., item frequencies, transitional probabilities, etc., to observe if, and how, this manipulation affects learning. Participants (infants, children, adults) are exposed to artificial languages under incidental exposure conditions, though there are many statistical learning studies in which exposure is intentional, i.e., participants are instructed to intentionally learn the meaning of novel words (e.g., Yu & Smith, 2007) or to monitor a continuous stream of speech to find out where the words begin and end (e.g., Newport & Aslin, 2004). The artificial languages often resemble natural languages more closely than the artificial grammars used in implicit learning research, using a lexicon consisting of pseudowords (*dingep*, *tha*, *vinoy*, *noo*) rather than letters, and phrase-structure grammars. In contrast to implicit learning research, statistical learning studies often do not include a measure of awareness. This is perhaps the most obvious methodological difference between implicit learning and statistical learning research. The implicitness of the acquired knowledge is generally assumed but not empirically verified (for exceptions see "The implicitness of implicit statistical learning", below).

The best-known paradigm in statistical learning research is the artificial speech segmentation task developed by Saffran et al. (1996). In this task, participants are exposed to a continuous speech stream (e.g., *bupadapatubitutibudutabapidabu* . . .) that consists of recurring pseudowords (here, *bupada, patubi, tutibu, dutaba, pidabu*, etc.). Importantly, the stream does not contain acoustic or prosodic cues to demarcate word boundaries; the only cues to word boundaries are the transitional probabilities between syllable pairs, which are higher within words (*bupa-, patu-, tuti-*) than between words (*-dapa-, -bitu-, -bapi-*). After exposure, participants are given a surprise test to determine if they are able to distinguish between the target items and pseudowords that did not occur during training (e.g., *batipa*, *dupitu*, *tipabu*).

Finally, cross-situational learning is another important paradigm in statistical learning research. In the classic version of this task (Yu & Smith, 2007), learners are presented with multiple objects on a computer screen (two, three, or four objects) while listening to sequences of pseudowords (two, three, or four pseudowords, depending on the number of objects), with no information as to which label goes with which referent. Critically, the presentation sequence of the pseudowords is unrelated to the positioning of the objects on the screen. To acquire the word-object mappings, learners thus have to keep track of potential referents and labels over multiple trials. In the cross-situational learning task developed by Monaghan et al. (2015), participants observe two dynamic scenes on the screen while listening to an artificial language sentence that describes only one of the scenes. No response was required during training. After training, the participants' task is to indicate, as quickly and accurately as possible, which scene the sentence refers to. Successful completion requires keeping track of statistical information across multiple learning trials.

## Critical issues and topics

### *The implicitness of implicit statistical learning*

The first studies on implicit learning concluded that the acquired knowledge was completely unavailable to consciousness, given that participants failed to report any rules underpinning the artificial grammar (e.g., Reber, 1967). This early view has been challenged and revised over the past decades.

It soon became clear that participants in AGL or sequence learning experiments might not be totally unaware of the underlying structure, with many participants frequently reporting partial knowledge of the artificial grammar or the repeating sequence in the debriefing session (e.g., Nissen & Bullemer, 1987; Reber & Lewis, 1977). However, it also became clear that this conscious (explicit) knowledge is generally insufficient to account for participants' performance during the training and test phases, i.e., the acquired knowledge tends to be richer than that which can be verbalized (e.g., Mathews et al., 1989; Reber & Lewis, 1977; Reber et al., 1980).

Early studies and interpretations have also been challenged on methodological grounds. There are well-known limitations to using verbal reports as a direct measure of awareness, which led to a debate concerning the implicitness of the knowledge acquired in AGL and sequence learning studies (for discussion, see Newell & Shanks, 2014) and, as a result, other behavioral measures of awareness have been proposed. For example, Dienes and Scott (2005) have advocated the use of subjective measures of awareness (e.g., source attributions). For each grammaticality judgment, participants are prompted to report whether the judgment was based on a guess, intuition, memory, or rule knowledge. If participants perform significantly above chance on grammaticality judgments that were based on guesses or intuition, this is taken as evidence for implicit knowledge. Above-chance performance on grammaticality judgments based on memory or rule knowledge is taken as evidence for explicit knowledge. A review of different awareness measures can be found in Rebuschat (2013) and Timmermans and Cleeremans (2015).

Despite the limitations of different awareness measures (see Rebuschat, 2013), the past decades of research have confirmed that participants in AGL and sequence learning experiments develop a knowledge base that is tacit and very difficult to verbalize. It is also clear that adult participants often develop both implicit (unconscious) and explicit (conscious) knowledge as a result of exposure (e.g., Guo et al., 2011). For example, when sequence learning data is reanalyzed based on participants' ability to explicate the underlying sequence, a learning effect is often observed in both aware and unaware participants (e.g., Curran & Keele, 1993; Monaghan et al., 2019). The fact that exposure to a complex structure could lead to both types of knowledge (implicit and explicit) should not come as a surprise; after all, we have at our disposal several ways of acquiring knowledge from the environment. The more interesting question, which has received too little attention until now, is how these learning processes interact, and how the specific task and exposure conditions affect the type(s) of knowledge we develop (see also Godfroid, 2023 [this volume]; Morgan-Short & Ullman, 2023 [this volume]; and the following).

Statistical learning experiments typically do not investigate whether exposure resulted in implicit or explicit knowledge, but this gap has recently been addressed by studies that added awareness measures. For example, Franco et al. (2011) found that participants acquired explicit knowledge while completing a speech segmentation task similar to that in Saffran et al. (1996). Batterink et al. (2015) measured explicit knowledge by means of a direct test (forced-choice recognition of syllable sequences, combined with subjective measures of awareness) and implicit knowledge by means of an indirect test (speeded syllable detection task). Results indicated that participants readily developed both types of knowledge, implicit and explicit, and that performance on the direct and indirect tests did not correlate, suggesting that implicit and explicit knowledge accrue in parallel and independently.

Hamrick and Rebuschat (2012) adopted the cross-situational statistical learning tasks developed by Yu and Smith (2007) and Monaghan et al. (2015) to investigate the incidental and intentional learning of pseudowords via cross-situational statistics. They found that participants in both groups developed both implicit and explicit knowledge. However, the exposure condition played an important role in the type of knowledge that participants acquired primarily. Under incidental exposure conditions, when participants were not informed about the learning target, they developed primarily implicit knowledge. In contrast, participants instructed to learn the pseudowords in the intentional exposure condition acquired primarily explicit knowledge. Interestingly, these participants also acquired some unconscious knowledge, highlighting the complex relationship between exposure condition (incidental vs. intentional) and acquired knowledge (implicit vs. explicit) (see also Guo et al., 2011; Rebuschat & Williams, 2012). Franco et al. (2016) also investigated the cross-situational learning of pseudowords but measured awareness by means of the process dissociation procedure (Jacoby, 1991) combined with subjective measures (Dienes & Scott, 2005). They confirmed that statistical learning does not necessarily occur unconsciously and that participants develop both implicit and explicit knowledge, even under intentional learning conditions. Finally, Monaghan et al. (2019) investigated the role of awareness in statistical learning. Participants learned novel words (nouns, verbs, function words) under incidental or instructed exposure conditions. Awareness was measured by means of retrospective verbal reports and subjective measures of awareness. They found significant learning effects in both unaware participants (those that were unable to verbally account for their performance) and in aware participants (those that reported partial knowledge of the learning target), with aware participants outperforming unaware participants in terms of learning rate and learning outcomes. It is clear that incidental and intentional learning tasks result in a complex mix of implicit and explicit knowledge, at least as revealed by subjective measures.

### *The role of attention in implicit statistical learning*

In an SLA context, implicit learning might be conceived as a process by which it is possible to automatically pick up aspects of a language. If we think of automatic processes as requiring relatively little attention (conceived as a limited processing resource), does this mean that implicit learning does not require attention?

Consider the question of learning under distraction (e.g., being exposed to a language while performing another attention-demanding task). In an AGL experiment, the participants' primary task is typically short-term recall of letter strings. If they are required to simultaneously hold random digits in working memory (Hendricks et al., 2013) or continuously generate random digits (Dienes & Scott, 2005) learning effects are not reduced. If the primary task is rule discovery then a secondary task can have a damaging effect, provided the system is simple enough to be learned explicitly (Waldron & Ashby, 2001; see also the following), but *implicit* AGL appears to be robust under dual task scenarios.

In contrast, auditory statistical learning of word boundaries appears to reduce to non-significant levels by highly attention-demanding secondary tasks such as monitoring a concurrent rapid picture sequence for repetitions (Toro et al., 2005). However, note that, unlike in the AGL task, in which participants are required to make responses to the letter strings (i.e., recall them during the training phase), no responses to the syllables are required in the statistical learning paradigm, and so they can effectively be ignored. What the elimination of the learning effect might tell us then is that a sufficiently demanding secondary task can withdraw attention from stimulus encoding if no responses are required, but not that the learning process itself requires attention.

The importance of attention in stimulus encoding is emphasized by Logan and Etherton's (1994) *obligatory encoding assumption*—"encoding into memory is an inevitable consequence of attending" (p. 1022). Conversely, there can be no encoding in memory without attention. They showed that novel associations between words could be learned incidentally so long as both words were attended; the learning effect disappeared if attention were oriented to just one of the words in advance. Hence, although there is evidence that attention is not required for immediate processing of familiar stimuli, there is good evidence that attention to stimuli is necessary for forming new associations (see Williams, 2013, for a review).

But it is not enough to attend to stimuli for learning relations between them; we have to attend to the relevant dimensions of those stimuli. In an ingenious SRT experiment (Jiménez & Méndez, 1999) a stimulus could appear at one of four positions (A, B, C, D) as determined by an artificial grammar. In addition, the *identity* of the stimulus varied (e.g., the sequence A-C-D would appear as ?-!-x). In fact, stimulus identity, as well as the AG, predicted the next stimulus position (in this example, ? predicts position C, ! predicts position D). Both the underlying AG and the predictiveness of stimulus identity could be simultaneously learned implicitly (without awareness of the regularities), but only when participants were required to keep a running count of character identities while completing the standard SRT task. Without this additional requirement, requiring the stimulus identities to be noticed, participants only learned the AG structure. Hence it is not sufficient to attend to stimuli for implicit learning to occur; we have to attend to them in the right way. Similarly, in another condition of their auditory statistical learning experiment, described previously, Toro et al. (2005) required participants to monitor the syllable stream for syllables of a relatively high pitch. The learning effect was again reduced to a non-significant level, even though the stream itself was being closely attended. This was presumably because participants were attending to the syllables in terms of their pitch rather than phonemes, which were the elements between which associations occurred.

What is important, therefore, is that the relevant stimuli, or stimulus dimensions, are noticed, and hence enter into awareness, but learners do not necessarily have to be aware of the role those stimuli play in the underlying system. This relates to Schmidt's (1994) distinction between *awareness* *at the level of noticing* (e.g., forms) and *awareness at the level of understanding* (e.g., rules that explain the distribution of forms). What the psychological literature suggests is that only the former is necessary for implicit learning of underlying regularities. How attention is allocated depends critically upon the task that the person is required to perform, and has a strong determining effect even on implicit learning. At the same time, the dual-task AGL studies show that the actual process of deriving the underlying regularities implicitly appears to operate with minimal demands on attention.

## *What is learned?*

What kinds of regularities have been shown to be learnable implicitly? Are there linguistic constraints on implicit learning, or can any regularity be acquired in this way?

There appears to be widespread agreement that some kind of implicit learning mechanism underlies the formation of *chunks*, e.g., multiword units in natural language, bigrams and trigrams in AGL, triplets of syllables in statistical learning. AGL studies have shown that test strings are more likely to be endorsed as grammatical if they share chunks with training items (Kinder & Assmann, 2000; Knowlton & Squire, 1996), and, in statistical learning, recall of syllable sequences has been shown to be chunk-based (Isbilen et al., 2020). The actual computations that produce these effects are clearly unconscious; chunking, as a basic memory process, therefore qualifies as a mechanism of implicit learning.

Non-adjacent dependencies (e.g., the association between "he" and "s" in "*he* walk/talk/ride-*s*") are one aspect of grammatical structure that goes beyond chunking. Studies have reported a failure to learn analogous dependencies between syllables in continuous streams (Newport & Aslin, 2004; Onnis et al., 2005). Other studies have reported more success but, in these cases, there was a phonological cue that distinguished non-adjacent and adjacent elements, e.g., plosive versus continuant syllables (Frost & Monaghan, 2016; Onnis et al., 2005) or mono- versus disyllabic nonwords (Gomez, 2002), or there was support from meaningful relations (Amato & MacDonald, 2010). This is an example of how the power of implicit learning is enhanced by the convergence between multiple cues, as is characteristic of natural languages.

Statistical learning studies have also revealed representational constraints on implicit learning. For example, lexical segmentation and vocabulary learning seem to be driven more by the patterning of consonants, such as the *p_r_g* pattern in *pu-ra-gi* and *po-re-gi*, than the patterning of vowels, such as the *u_e_a* pattern in *ku-me-pa* and *ru-me-ta* (Bonatti et al., 2005; Nazzi & Cutler, 2019). In contrast, abstract patterns are more learnable when instantiated over vowels than consonants (e.g., the ABA structure over the vowels in *ta-pe-na* versus the consonants in *ba-nu-be*) possibly reflecting the privileged status of vowels in conveying grammatical information, at least in the first language(L1)s of the participants tested (Toro et al., 2008). Rats do not show differential sensitivity to regularities over vowels and consonants (de la Mora & Toro, 2013). Hence, it is not the case that we pick up any and all regularities in the input, but our sensitivity to statistical patterns is conditioned to some extent by our prior linguistic knowledge and expectations, which can actually make us "deaf" to some patterns (Endress & Hauser, 2009).

The foregoing studies represent rather synthetic abstractions from natural languages. Other studies have explored implicit learning of more obviously linguistic, and rule-like, phenomena and, unlike in statistical learning research, with more emphasis on whether linguistic regularities can be acquired without awareness at the level of understanding. Such studies have shown implicit learning of phonotactic constraints (Dell et al., 2000) and stress patterns (Chan & Leung, 2014; Graham & Williams, 2018). In the domain of syntax, semi-artificial language learning studies have shown implicit learning of phrasal patterns, such as the characteristic verb placement in German (Rebuschat & Williams, 2012). Other studies have shown implicit learning of semantically conditioned rules, such as whether the novel determiners *gi* and *ro* are used before animate or inanimate nouns (Batterink et al., 2014;

Chen et al., 2011; Kerz et al., 2017; Leung & Williams, 2012; Williams, 2005), though the effect using the Williams (2005) paradigm, or similar, has not always been obtained (Andringa, 2020; Hama & Leow, 2010) for reasons that are as yet unclear. Other studies have shown implicit learning of semantic preference rules—whether the novel verbs *gouble* and *powter* are followed by concrete or abstract nouns (Paciorek & Williams, 2015a, 2015b). However, as in other areas of implicit learning, the acquisition of semantics-based generalizations does not appear to be unconstrained. Studies have failed to find implicit learning effects for regularities based on relative size (Chen et al., 2011; Leung & Williams, 2012) and Leung and Williams (2014) only found significant learning effects for a long-flat distinction in Chinese-speaking participants (where this distinction is encoded by classifiers). Such studies demonstrate the differential availability of conceptual distinctions for grammaticization, either due to the participants' native language, language universals, or salience in the input, as has been shown for the relative size distinction (Pham et al., 2020). Therefore, while studies have demonstrated implicit learning of natural language phenomena relating to phonology, syntax, and grammatical form-meaning connections, it has become increasingly evident that the learning process is constrained.

## *Do implicit and explicit learning, knowledge, and instruction interact?*

If implicit learning is an automatic process, the question arises as to how it might interact with, or be affected by, any conscious learning strategies that a learner might employ, either spontaneously or as a response to instruction. This issue has been discussed in the SLA literature in terms of either a strong interaction between explicit and implicit learning (whereby they influence each other directly), as opposed to a weak interaction (mediated, for example by attentional processes), or complete independence (see Godfroid, this volume, for a discussion of the *interface* issue in SLA). Here we focus on studies using implicit learning paradigms which, although examining artificial systems, we believe offer useful and generalizable insights.

Most research has focused on the effect of instructions to search for rules and how that might impact underlying implicit learning. As one would expect, if a regularity is relatively simple, then rule discovery will boost learning (Mathews et al., 1989). For more complex systems, such as those used in AGL, early results suggested that participants given rule search instructions performed worse than those given a memorization task (Reber, 1976). However, subsequent studies failed to find any difference between intentional and incidental learners using artificial grammars (Dienes et al., 1991; Mathews et al., 1989). The weight of evidence, therefore, suggests that conscious attempts to work out a complex system do not add anything over and above what is acquired by passive, implicit, learning. But at least trying is not detrimental, perhaps because participants simply can't develop coherent hypotheses.

But there may be other situations in which trying hurts. In the SRT task, the difficulty of discovering the sequence can be increased by interspersing the sequenced items with random events; for example, a simple sequence such as 1,4,2,2 becomes 1,R,4,R,2,R,2,R (in which numbers represent possible screen positions and R represents randomly generated positions). Using this "alternating" SRT, Fletcher et al. (2005) found that simply telling participants that there was a repeating sequence eliminated the learning effect. They suggest that this was because the participants actually looked for patterns involving adjacent elements, which is the most natural way of interpreting what a "sequence" might be. In line with this, Howard and Howard (2001) found that telling participants that there was an alternating pattern (but not what it was) did not impair learning, at least in young adults, but it did not improve it either (see the following for why this might be). Efforts to learn may be harmful because attention may be directed to the input in the wrong way, according to naïve assumptions about the domain, warping the data that enters the implicit learning mechanism, amounting to a negative effect of weak interaction.

Of course, even without any instructions to do so, some participants may spontaneously look for structure. Could creating conditions that reduce the likelihood of this increase implicit learning effects? Hypnosis disturbs executive function, and hence should suppress explicit learning activity, and it has been found that using the alternating SRT task, learning effects were 2.5 times greater under hypnosis than in the normal alert state (Nemeth et al., 2013). Interestingly, the improvement was actually confined to participants with high executive function, suggesting that this is the group that are most likely to try to spontaneously figure out a system, and so they benefit the most from interventions that suppress that tendency.

In cases in which conscious hypotheses are more likely to be helpful, could learning be boosted by combining implicit and rule search tasks together? In Mathews et al. (1989) participants were trained on a relatively simple artificial grammar that some people are able to work out under rule-search instructions. Different groups of participants performed different combinations of implicit (memorization) and explicit (rule-discovery) tasks during training, followed by a GJT. The best (in fact near-perfect) GJT performance was obtained when participants performed the implicit task in the first half of training, followed by the rule-discovery task in the second half. This combination was far more effective than either explicit or implicit training alone, or explicit training in the first half followed by implicit training in the second. The authors argue for a synergy between implicit and explicit learning modes, leading to over-additive learning effects, suggestive of a strong interaction. However, implicit training on its own led to no significant learning, and so it is hard to see what kind of knowledge the explicit process could have been interacting with. One possibility is that the memorization task allowed the participants to build up a store of exemplars, or fragments, that facilitated subsequent rule discovery through conscious recall. In this view, there was no actual facilitation from implicit knowledge of the underlying grammar system, and no interaction between implicit and explicit learning processes.

All of the foregoing studies examined explicit learning in the sense of rule discovery. But what about explicit instruction? Can this have an impact on the implicit learning process? In Reber et al. (1980) participants were shown a diagram of a complex AG, with an explanation of how it was used to generate five example grammatical strings. This treatment on its own resulted in a relatively low level of GJT performance (presumably because the instructional information was not fully internalized), which was equivalent to that obtained after implicit training in the form of passive observation of 63 example strings. However, combining instruction with implicit training significantly improved GJT performance. The authors argue that instruction "served to establish cognitive 'boundaries' for the tacit induction operations engaged during the observation [implicit training] period" (ibid., p. 500, our addition). This implies at least a "weak" form of interaction between explicit knowledge and implicit learning whereby conscious knowledge guides implicit learning through the appropriate allocation of attention to the stimuli (see "The role of attention in implicit statistical learning", above). However, given that the implicit task was passive observation, we cannot rule out that participants were actually engaging in rule discovery, especially since they were informed that they would subsequently be asked questions about the strings. Without additional procedures that reduce contamination from explicit learning processes (e.g., a demanding secondary task) it cannot be claimed that instruction affected implicit learning as such.

There are also general boundary conditions on the usefulness of explicit information. One is the learners' ability to remember it (as illustrated by Reber et al., 1980). The other is the time required to mobilize it, since this depends on controlled processing. For example, in Sanchez and Reber's (2013) SRT study, participants who memorized the sequence through observation in a pretraining phase showed the same learning effects, as measured by actual SRT performance, as a non-instructed group, despite showing superior conscious knowledge of the sequence following training. Presumably, conscious knowledge could not be mobilized quickly enough to affect this speeded task. But what is interesting is that simply knowing that there was a repeating sequence did not facilitate subsequent implicit learning, something that might have been expected on a weak interaction position.

These studies provide an indication of the difficulties of addressing interactions between implicit and explicit knowledge and learning processes even within the apparently tightly constrained environment of implicit learning experiments. The challenge is to show that it is precisely implicit knowledge that interacts with explicit learning (e.g., rule discovery), or that explicit knowledge (e.g., from instruction) actually influences implicit learning, either directly or indirectly. However, what is relatively clear is that consciously attempting to work out a simple system can be beneficial, and for complex systems it will be either neutral or damaging, depending on whether it results in a counterproductive allocation of attention. Providing explicit information may have no effect if the task is speeded, and there is no convincing evidence from these studies that it has even an indirect effect on implicit learning. Clearly, there is scope for exploring these issues further using implicit learning paradigms (see Textbox 23.2).

## Current trends and future directions

### *Individual differences*

Although Reber (1993) originally claimed that implicit learning should be relatively invariant across individuals, participants in implicit and statistical learning studies clearly show differential learning effects. Recent research suggests that this variation is meaningful in that it can be related to individuals' sensitivity to the probabilistic structure of natural language (Conway et al., 2010; Divjak & Milin, 2020), and to specific sentence processing measures (Misyak & Christiansen, 2012). These studies suggest that there is a common underlying implicit statistical learning ability engaged in laboratory tasks and both adult and child (Kidd, 2012) language acquisition.

### *Consolidation*

In recent years there has been an explosion of interest in the role of sleep in memory consolidation. Sleep, even if only a brief nap, has been shown to enhance implicit learning of phonotactic constraints (Gaskell et al., 2014), retention of statistical information (Durrant et al., 2011), and learning of abstract structure in both statistical learning (Gomez et al., 2006) and AGL (Nieuwenhuis et al., 2013). These studies are important in showing how single-session lab studies might actually underestimate the power of implicit learning over an extended time (also see MacWhinney, 2023 [this volume]).

**Textbox 23.2 Open questions and issues**

Do constraints on implicit learning derive from general cognition or domain-specific knowledge? Does the nature of the L1 influence what can be learned implicitly? Are there universal constraints on implicit learning?

How do exposure conditions (incidental, intentional, instructed) affect the development of implicit and explicit knowledge?

What is the basis of individual differences in implicit learning ability?

What is the role of sleep in implicit learning, especially in relation to the emergence of generalizations (and, potentially, the emergence of conscious knowledge)?

Implicit learning experiments usually reveal effects in receptive tasks after brief exposure. How does this relate to the kind of knowledge that underlies fluent language production in a second language?

## Further reading

Christiansen, M. H. (2019). Implicit statistical learning: A tale of two literatures. *Topics in Cognitive Science*, *11*, 468–481.

An article that charts the development of the two research strands, implicit learning and statistical learning, from their inception to the present day.

Frost, R., Armstrong, B., & Christiansen, M. (2019). Statistical learning research: A critical review and possible new directions. *Psychological Bulletin*, *14*5(12), 1128–1153.

A critical appraisal of the last two decades of statistical learning research, covering key theoretical and methodological issues.

Monaghan, P., & Rebuschat, P. (Eds.). (2019). Aligning implicit learning and statistical learning: Two approaches, one phenomenon. Special issue of *Topics in Cognitive Science*, *11*(3).

A special issue that brings together leading researchers from implicit learning and statistical learning to encourage the formulation of joint research agendas.

Rebuschat, P. (2013). Measuring implicit and explicit knowledge in second language research. *Language Learning*, *63*(3), 595–626.

A review of several measures of implicit and explicit knowledge, their respective limitations, and basic guidance on their application.

Williams, J. N. (2009). Implicit learning in second language acquisition. In W. C. Ritchie & T. K. Bhatia (Eds.), *The new handbook of second language acquisition* (pp. 319–353). Emerald Press.

A thorough review article on implicit learning and its role in second language acquisition.

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