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Implicit Learning and Language Acquisition

Three Approaches, One Phenomenon

Patrick Rebuschat

Introduction

Language acquisition is frequently cited as an example of implicit learning "outside the lab" (Frensch & Rünger, 2003; Reber, 1967, 2011, this volume), and it is easy to see why this is the case. After all, infants and young children do not set out to intentionally memorize thousands of words or to consciously discover the rules or patterns of the language(s) in their environment. Instead, young learners acquire language largely incidentally, i.e., without the intention to learn, and as a byproduct of substantial exposure to input and interaction with caretakers and other speakers. Moreover, the knowledge that learners develop as a result of this process is largely tacit and inaccessible to conscious introspection, but enables them to communicate effectively and without effort. The close association of implicit learning and language acquisition can be traced back to Arthur Reber's (1967) seminal study. When designing his first artificial grammar learning (AGL) experiments, Reber aimed to create "a mini-environment that could function as a platform to examine natural language learning" (Reber, 2015, p. vii), and the empiricist concept of implicit learning was introduced in 1967 in opposition to Chomsky's (1965) linguistic nativism (see Reber, this volume, for detailed discussion). The process of learning a new language certainly bears many of the characteristics of implicit learning, and Reber (2011) presents a convincing case for why implicit learning could function as a general learning mechanism capable of handling the acquisition of natural languages.

Artificial grammar research has substantially advanced our understanding of the fundamental cognitive and neural processes involved in learning and memory (Batterink et al., 2019; Williams, 2020), but, at the same time, we cannot assume that the important insights gained from AGL studies directly apply to the acquisition of natural languages (Schmidt, 1994). For example, the miniature

Patrick Rebuschat, *Implicit Learning and Language Acquisition* In: *The Cognitive Unconscious*.
Edited by: Arthur S. Reber and Rhianon Allen, Oxford University Press. © Oxford University Press 2022.
DOI: 10.1093/oso/9780197501573.003.0006

systems used in artificial grammar research tend to be much simpler than natural languages, and they lack a semantic dimension. Given that language acquisition entails learning to process semantic information encoded in (linguistic) symbols, the use of meaningless stimuli (letter strings, pseudowords, etc.) in much of implicit learning research could limit its generalizability to the study of how we learn natural language. The training periods in AGL experiments are relatively short and input-based, i.e., participants are generally not expected to use the grammar productively as part of the training. Participants usually do not achieve very high levels of proficiency, and delayed posttests are rarely included as part of the design, which means we know too little about the long-term retention of knowledge. In contrast, language learning takes years of exposure and involves not just language comprehension but also production. In the case of child language acquisition, the typical outcome is native proficiency, not just above-chance performance in a classification task. Finally, AGL studies primarily test adults, whereas natural languages are learned across the lifespan, by infants and children as well as younger and older adults.

It is clear that artificial grammar and sequence learning studies on young, college-educated adults can only provide us with part of the picture (Howard & Howard, this volume). As the contributions in this volume beautifully illustrate, a more comprehensive understanding of implicit learning requires us to move beyond the theoretical and methodological boundaries of our own disciplines and consider additional types of evidence. When it comes specifically to our understanding of the role of implicit and explicit learning in language acquisition, this complementary evidence can be found in (at least) three distinct research strands, *implicit learning*, *statistical learning*, and *second language research* (Rebuschat, 2015). The aim of this chapter is to introduce readers to these strands, to illustrate what each can contribute, and to highlight research themes that are of mutual interest. Over the past decade, several symposia, conferences, edited books, and special journal issues (Andringa & Rebuschat, 2015; Monaghan & Rebuschat, 2019; Rebuschat, 2015; Rebuschat & Williams, 2012a; Sanz & Leow, 2011) have brought together colleagues from diverse disciplinary backgrounds (e.g., linguistics, cognitive psychology, neuroscience, education) who share an interest in implicit learning and language acquisition but whose paths otherwise wouldn't have crossed. The fruitful interactions that resulted from these efforts suggest that the advancement of our understanding of implicit learning and language acquisition can benefit greatly from more substantial interaction across disciplines and research communities. I hope this chapter facilitates this interaction by highlighting similarities and differences across strands and by pointing out complementary lines of investigation.

Three Approaches, One Phenomenon

Implicit learning as a research strand in cognitive psychology began with the AGL experiments conducted by Reber and colleagues. (See Frensch & Rünger, 2003; Perruchet, 2008; Reber, 1993, for reviews.) However, these were neither the first, nor the only studies to employ finite-state grammars to investigate aspects of human cognition (Reber, this volume). Roughly around the same time, several researchers began employing artificial systems in order to investigate language acquisition (e.g., Braine, 1963; Segal & Halwes, 1966). This separate strand of research later emerged as a major line of inquiry within developmental psychology, and in its present guise of statistical learning (Saffran et al., 1996) continues to make fundamental contributions to our understanding of how languages are learned.

Statistical learning, i.e., the process of learning from the distributional properties in the environment, entails computations based on units or patterns (sounds, syllables, syntactic categories, etc.). Research on statistical learning frequently involves infant or child language learners, though studies with adult participants are very common. (See Frost et al., 2019; Saffran & Kirkham, 2018, for reviews.). Both lines of research, implicit learning and statistical learning, investigate how we acquire information from the environment, and both rely heavily on the use of artificial systems. Given these and other similarities, Perruchet and colleagues (Perruchet, 2019; Perruchet & Pacton, 2006) suggested that these distinct lines of research actually represent two approaches to a single phenomenon. Conway and Christiansen (2006) went a step further and combined the two approaches in name, *implicit statistical learning*, a proposal that is congruent with the fact that definitions of implicit learning and statistical learning often emphasize the distributional nature of the learning mechanism (Frensch & Rünger, 2003; Frost et al., 2019; Reber, 2011).

Research on implicit (statistical) learning is not restricted to the two research strands above. The field of second language acquisition (SLA), for example, has a long-standing interest in the topic of implicit and explicit learning. (See DeKeyser, 2003; N. Ellis, 2007; Leow & Donatelli, 2017; Williams, 2009, for reviews.). Over the past 40 years, three related questions have received considerable attention and yielded a substantial amount of empirical research. The first question concerns the role of awareness in language acquisition and the possibility of learning without awareness (Schmidt, 1990). The second question is methodological and concerns the measurement of awareness. Here, a significant number of studies have investigated ways to measure awareness at the time of encoding (Leow, 1998) and awareness of what has been learned (R. Ellis, 2005). That is, studies have either tested awareness during the learning process (while participants were engaged in the training task) or awareness of the learning product (measured during the test phase). The third question concerns the implicit-explicit interface, i.e., the question of whether (and how much) explicit learning and knowledge (e.g., in the form of metalinguistic rules) influence the development of implicit knowledge of language (N. Ellis, 2007; Godfroid, in press).

To better understand how each of these research strands informs our understanding of implicit and explicit learning in language acquisition, to identify what each can contribute, and to emphasize how these perspectives are essential and complementary, it is helpful to compare the strands along a few key research dimensions. The summary below is necessarily broad, and there are certainly notable exceptions to the rule, but I think the descriptions are generally representative at the time of writing. For discussion of methodological issues in statistical learning research, see Frost et al. (2019) and Siegelman et al. (2016). In the case of experimental SLA research, several meta-analyses provide helpful descriptions of methodological features (Goo et al., 2015; Kang et al., 2018; Norris & Ortega, 2000; Sok et al., 2019; Spada & Tomita, 2010).

Primary Research Focus

The primary research focus in each strand is on learning, but there are important differences in emphasis and scope. Traditionally, in implicit learning research the focus has been on the general properties of learning and memory. Miniature systems are used to uncover fundamental aspects underlying our ability to rapidly acquire information from complex stimulus domains, and it is argued that these insights are directly relevant to the development of complex behaviors such as music cognition (Rohrmeier & Rebuschat, 2012), language comprehension and production (Reber, this volume), social cognition (Kurdi & Banaji, this volume), reasoning (De Neys, this volume), and intuitive decision-making (Allen, this volume). In contrast to implicit learning, the scope of most statistical learning research is traditionally narrower, concentrating primarily on the acquisition of a very specific domain, namely language (Romberg & Saffran, 2010). As mentioned above, this is due to the fact that statistical learning represents the continuation of a long line of research in developmental psychology that used artificial systems to investigate language acquisition. Despite this initial focus on language, it is interesting to note that the scope of statistical learning has been broadening substantially, aligning this research strand more closely with implicit learning. Many studies have investigated general properties of learning, as can be seen, for example, in the systematic exploration of visual statistical learning and of the domain-generality of statistical learning (see Frost et al., 2019). This trend is particularly clear in a recent special issue on future directions in statistical learning (Armstrong et al., 2017), which evaluates the promise of statistical learning as a more comprehensive theory of learning and information processing across various domains of cognition. Finally, in second language research, the scope of inquiry is narrower by definition. SLA focuses exclusively on *language* learning (and not on learning in general) and within language learning the focus is on the acquisition of novel languages once the native language(s) have been established, i.e., second, foreign, or additional language learning.

Participants

When it comes to participants, we find that the three strands rely heavily on the testing of adult participants, presumably because these are the most readily available and testable population. In statistical learning, we also find a substantial number of studies with infants and young children (Saffran & Kirkham, 2018). These studies (e.g., Gómez, 2002; Saffran et al., 1996; Smith & Yu, 2008) tend to be particularly influential, given that they provide the essential proof of concept that statistical learning can play a role in language acquisition. Second language studies also occasionally test child learners, but this is certainly rarer. The majority of SLA participants are adults. It is interesting to note that, even though statistical learning and SLA research usually investigate how adult participants learn a novel language (artificial or natural), in the former case these studies with adults are said to inform our general ability to learn language, whereas in the latter case studies are clearly seen as a case of *second* language learning. Given that, strictly speaking, statistical learning studies with adults are studies in additional language learning, it is clear that statistical learning and second language research could benefit from much closer ties, with statistical learning contributing to our understanding of fundamental processes of adult language learning and SLA research contributing an applied perspective that is often missing in statistical learning research. Finally, implicit learning paradigms have also been extensively used in research on animal cognition (e.g., Rey et al., 2019; ten Cate, 2014), but this line of inquiry is nonexistent in SLA research.

Experimental Design

Experiments in implicit and statistical learning are often short, lasting less than an hour, and follow a single shot, posttest-only design. Learning effects can be rapidly observed and reliably elicited by means of a variety of tasks and across a range of populations, from infants and children to adults and nonhuman primates. Pretests are usually not included, because participants are unlikely to have encountered the artificial language before. Delayed posttests (administered days or weeks after exposure) are often not part of the design, and neither are control groups, given that learning in the experimental group can be measured by comparing participants' performance to chance. When control participants are included, these are either untrained, i.e., they complete the test but do not complete any training task, or they are trained on random sequences before given the posttest (see Hamrick & Sachs, 2018, for discussion). This relative ease of administration partially accounts for the widespread popularity of different implicit and statistical learning paradigms in psychology and neuroscience, but it also reminds us that these studies contribute especially to our understanding of *ab initio* learning and the earliest stages of language acquisition. Further, the short training periods and the absence of delayed posttests could also lead us to underestimate the size of learning effects (and thus of implicit learning). This is because language acquisition requires substantial amounts of input, which might be insufficiently provided in short exposure sessions, and because there is evidence that, occasionally, learning effects might not be registered in the immediate posttest but detected in delayed posttests (e.g., Grey et al., 2014; Walker et al., 2020).

In contrast, experiments in SLA often follow a pretest-posttest design, with multiple treatments administered over several days to train participants on the learning target (generally a natural language). In addition to an immediate posttest, studies often include a delayed posttest, which is administered one or two weeks after the immediate posttest. SLA experiments focus on different proficiency levels, from beginners to advanced speakers, and studies on *ab initio* learning are comparatively rare (see Indefrey & Gullberg, 2010). Typically, even low-proficiency participants have already had several hours of L2 exposure. Since participants might be exposed to the learning target (L2 English, L2 Spanish, etc.) outside the lab, control groups are usually included as part of the design. Control participants tend to receive training on the learning target under incidental exposure conditions; this usually provides us with an important baseline of how much participants can learn by mere exposure. Experimental participants, in contrast, are trained on the same target by means of different implicit or explicit interventions.

Training Phase: Experimental Tasks, Learning Targets, and Exposure Conditions

When it comes to the training phase, it is helpful to compare the three strands with regard to the preferred experimental tasks, learning targets, and exposure conditions. The two most recognizable tasks in implicit learning are the AGL task and the serial reaction time (SRT) task (Nissen & Bullemer, 1987). The traditional learning targets in the former case are meaningless letter strings (TPTS, VXXVPS, etc.) generated by a finite-state grammar, and in the latter case 10- or 12-digit sequences that determine the positioning of a target symbol and to which participants have to respond. Participants are typically trained under *incidental* exposure conditions, i.e., they are informed neither about the existence of the learning target nor that they will be tested on the acquisition of the target. There is a significant number of AGL and SRT studies that directly contrast incidental and intentional exposure conditions, but the default exposure mode in most implicit learning research is incidental, presumably because implicit learning is more likely to be observed when participants are not actively trying to figure out the learning target (Reber, 1993, p. 26).

Classic statistical learning tasks include the auditory statistical learning (ASL) task, which is used to investigate our ability to use statistical cues to segment a continuous stream of polysyllabic pseudowords (Saffran et al., 1996), and the cross-situational learning (CSL) task, which is used to research our ability to keep track of statistical information across multiple learning trials (Yu & Smith, 2007). The ASL and CSL tasks have been used primarily (but not exclusively) to study aspects of word learning. In addition, statistical learning studies have used artificial languages to study the usefulness of statistical cues to acquire syntactic features (Gómez, 2002). Unlike AGL research, these artificial systems resemble natural languages more closely, using phrase-structure grammars (Saffran, 2001) rather than finite-state systems and pseudowords (e.g., *Tha makkot noo pakrid*; Monaghan et al., 2019) rather than letter or tone sequences. Statistical learning studies with infants require the use of incidental exposure conditions, but with older children and especially adults, it is common to find studies that train participants under *intentional* exposure conditions. For example, participants might be asked to intentionally learn the meaning of novel words (Smith & Yu, 2008) or to monitor a continuous stream of speech to find out where the words began and ended (Newport & Aslin, 2004). This choice is perhaps surprising, given that much, perhaps most, of language learning in childhood occurs incidentally. If we are using artificial languages as a model of what happens in the wild, then it would make sense to use the exposure conditions that are more frequent outside the lab. As Reber (1993) points out, this intentional stance might also make it less likely for implicit learning to observed. In recent years, there has been growing awareness within the statistical learning community that exposure condition (incidental vs. intentional) affects how learning takes place (see Arciuli et al., 2014; Hamrick & Rebuschat, 2012; Kachergis et al., 2014; Monaghan et al., 2019), which might lead to the more frequent adoption of incidental exposure conditions and thus to a closer methodological alignment of implicit and statistical learning research.

SLA research cannot be readily identified with a few unique tasks; the field is simply too diverse and too broad for this (see Sok et al., 2019, for synthesis). Most SLA research focuses on the acquisition of natural languages, thus complementing artificial systems research in implicit learning and statistical learning. The most widely studied natural languages are predictably L2 English and L2 Spanish, but there are many interesting studies that employ less-frequently studied L2s as learning targets, including Latin (Graham & Williams, 2018; Stafford et al., 2010), Samoan (Robinson, 2005), and Welsh (N. Ellis, 1993). In addition, many experimental SLA studies have used artificial or semiartificial languages, which blend artificial and natural language characteristics. Some languages have a lexicon consisting of pseudowords (Morgan-Short et al., 2011), others a lexicon consisting of words from the participants' native languages (Rebuschat & Williams, 2012b), but in either case the underlying morphology or syntax is usually based on that of natural languages that the participants have not learned yet, including Czech (Bovolenta, 2019; Rogers et al., 2016), German (Bell, 2017; Gao & Ma, 2021), Japanese (Grey et al., 2014), Persian (Hamrick, 2014), and Spanish (Morgan-Short et al., 2011). Most of this research has focused on the acquisition of morphology or syntax, but there are also studies investigating the implicit and explicit learning of phonological, lexical, and semantic information (Chan & Leung, 2018; Graham & Williams, 2018; Paciorek & Williams, 2015; Sonbul & Schmitt, 2013; Toomer & Elgort, 2019).

Finally, in experimental SLA research, there is a long tradition of systematically and rigorously exploring the effects of different exposure conditions on learning. This exploration includes the comparison of incidental and intentional exposure conditions but extends this significantly to examine the effect of other relevant variables, such as individual learner characteristics and the role of task type. In meta-analyses (e.g., Norris & Ortega, 2000; Spada & Tomita, 2010), training tasks are usually coded as "implicit" if the task required participants to focus primarily on the meaning of the stimuli and neither metalinguistic rule presentation nor directions to attend to particular language forms were part of the task instructions. An implicit training task might simply require participants to read a text in which the learning target occurs (e.g., the English past tense *-ed*) but with instructions that require them focus on the meaning of the text (and not on the learning target) in order to reply to a few comprehension questions afterward. This baseline condition tells us how much can be learned by exposure alone. Training tasks are coded as "explicit" when participants are required to attend to particular linguistic forms in the input (e.g., the past tense *-ed*) or when they are either presented with metalinguistic rules or instructed to arrive at metalinguistic generalizations on their own (e.g., the rule that describes the formation of the regular past tense in English). The "implicit" and "explicit" conditions in SLA research are conceptually similar to the incidental and intentional exposure conditions in implicit and statistical learning research, in the sense that the learning target is hidden in the former and overt in the latter. An important difference is that implicit and explicit conditions in SLA also tend to manipulate whether and how much the focus of attention is on the *meaning* of the linguistic stimuli (what is being said) or on their *form* (how it is being said). What differentiates implicit treatments (e.g., input flood, input enhancement, recasts) from explicit ones (e.g., consciousness-raising, processing instruction, and metalinguistic feedback) is how frequently attention shifts from meaning to form (and back again).

Test Phase: Measuring Learning and Awareness

Regarding the assessment of learning, researchers across the three stands have relied extensively on *retrospective* measures of learning, i.e., on tasks that are administered after the completion of training. This is generally done during the test phase by means of different behavioral tasks that measure participants' ability to distinguish test items that are licensed by the artificial grammar from those that don't (grammaticality judgments, 2AFC, etc.). Many of these tasks require adult participants to make an overt response (*Is the sequence grammatical? Which of the two words was present in training?* etc.), which has led to the suggestion that the knowledge measured in these reflection-based tasks is more likely to tap into explicit knowledge (Christiansen, 2019). To measure implicit knowledge more reliably, researchers have advocated the use of more indirect measures (those that do not require an overt response), including the use of eye tracking (e.g., Andringa, 2020), electroencephalography (e.g., Batterink et al., 2015; Morgan-Short et al., 2011), or processing-based behavioral tests (e.g., Granena, 2013; Isbilen et al., 2020). These measures could have the additional advantage of being more sensitive to learning effects. For example, when studies include multiple measures of learning in the design (e.g., recording behavioral and electrophysiological responses during grammaticality judgments, e.g., Tokowicz & MacWhinney, 2005) the learning effect is sometimes only detected via the indirect measure but not in the direct one (for review, see Williams & Paciorek, 2015).

In recent years, there have been increasing calls for the additional use of *concurrent* measures of learning, i.e., tasks that measure learning as it unfolds during the training phase (Christiansen, 2019; Monaghan et al., 2019). In implicit learning research, the SRT task has been doing precisely that, of course, but it is still rare for researchers to measure learning during the training phase of the AGL task (see Reber, 1967, Experiment 1, for an early exception). Among the more recent exceptions is Misyak et al. (2010), who combined the SRT and AGL paradigms in their study of nonadjacent dependency learning, demonstrating the advantages of measuring AGL during the training phase. In statistical learning research, too, researchers have been developing concurrent measures of learning. Recent examples are the target-detection tasks used to track learning during the ASL task (Batterink et al., 2015; Franco et al., 2015) and the novel CSL task used by Monaghan and Rebuschat (Monaghan et al., 2019, 2021; Rebuschat et al., 2021; Walker et al., 2020). Examples of concurrent measures used in second language research include the reaction-time paradigm in Leung and Williams (2012) and the visual-world paradigm used by Andringa (2020). The comparison of concurrent and restrospective measures of learning, collected by means of behavioral tests, eye tracking, EEG, or other elicitation methods (see Godfroid et al., 2015; Morgan-Short et al., 2011), promises to further characterize implicit and explicit processes during learning and testing.

To conclude, we also need to consider how the three strands deal with the issue of awareness. In implicit learning research, the experimental arrangements generally include a measure of awareness to determine whether the acquired knowledge is conscious or not; in fact, one could argue that this is a defining methodological feature of implicit learning studies. This is frequently done by prompting participants, at the end of an AGL or SRT experiment, to report any rules or patterns they might have noticed during the training or testing phases. If participants fail to report relevant knowledge, they are judged to be unaware of the knowledge underpinning test performance. Retrospective verbal reports have been widely used, but there are well-known limitations to using verbal reports as a measure of awareness (Newell & Shanks, 2014). As a result, other behavioral measures of awareness have been proposed and applied to implicit learning research (see Rebuschat, 2013; Timmermans & Cleeremans, 2015, for reviews). For example, Dienes and Scott (2005) have advocated the use of subjective measures of awareness, while others have proposed the contrastive use of direct and indirect tests (Jiménez et al., 1996) or adapted Jacoby's (1991) process dissociation procedure (PDP) to estimate the existence of conscious and unconscious knowledge in AGL and sequence learning (e.g., Destrebecqz & Cleeremans, 2001).

In contrast, statistical learning experiments usually do not include measures of awareness; for a long time, it has been simply assumed that the acquired knowledge is implicit. In part, the lack of an awareness measure can be explained by the fact that infants and very young children are incapable of providing verbal reports, indicate confidence levels, or perform on fragment-completion tasks. However, many statistical learning studies use adult participants, which means that basic measures of awareness could be administered. Over the past decade, there has been growing awareness of this potential shortcoming, and several studies have now addressed the issue of awareness in statistical learning (see the special issue on the role of awareness in statistical learning, edited by Franco and Destrebecqz, 2014). For example, Franco and colleagues used PDP (Jacoby, 1991) to determine whether participants developed implicit or explicit knowledge during the ASL task (Franco et al., 2011) and the CSL task (Franco et al., 2016). Rebuschat, Monaghan, and colleagues have used verbal reports and subjective measures to investigate awareness during CSL (Hamrick & Rebuschat, 2012; Monaghan et al., 2019). Other statistical learning researchers, rather than adding awareness measures to their design, have introduced novel measures of learning that are more likely to tap into implicit knowledge, either via behavioral or electrophysiological measures (e.g., Batterink & Paller, 2017; Isbilen et al., 2020).

In SLA research, on the other hand, the issue of awareness has played a central role for the past 40 years (see DeKeyser, 2003; N. Ellis, 2007; Leow & Donatelli, 2017; Schmidt, 1990; Williams, 2009, for reviews). As mentioned, we can distinguish different lines of inquiry. On the one hand, there are many SLA studies that investigate the role of awareness at the time of encoding. These frequently measure awareness by means of concurrent verbal reports (think-aloud protocols) during the training or test task, a method pioneered by Leow (1998), or by recording eye movements, a method widely promoted by Godfroid and colleagues (Godfroid, 2020). On the other hand, a significant number of SLA studies investigate whether training results in implicit or explicit knowledge (see Goo et al., 2015; Kang et al., 2018; Spada & Tomita, 2010, for syntheses). A key development here was the publication of R. Ellis (2005), a psychometric study that validated a battery of tests to reliably distinguish implicit and explicit language knowledge. The test battery consists of five tests, three of which measure implicit knowledge (elicited imitation, oral narration, timed grammaticality judgments) and two explicit knowledge (untimed grammaticality judgments, metalinguistic knowledge test). These tests are freely available and have been widely used in the SLA community, thus facilitating comparison across studies. The publication of R. Ellis (2005) also resulted in a fruitful and ongoing empirical discussion about the best way to measure implicit and explicit knowledge of language. For example, Suzuki (2017; Suzuki & DeKeyser, 2015) has questioned the use of elicited imitations to measure implicit knowledge, suggesting that this task might actually tap into automatized explicit knowledge instead.[1] Following an important trend in SLA toward the use of psycholinguistic tasks to measure learning (Jiang, 2012), several researchers have proposed the use of processing-based tests (word monitoring, self-paced reading, visual-world paradigm, etc.) to measure implicit

[1] It is not quite clear whether time pressure actually increases the probability of participants drawing on implicit knowledge. The idea that fast responses necessarily reflect unconscious knowledge has been questioned in domains other than language as well, see, for example, the discussions of the decision-making and reasoning literature in Allen (this volume) and De Neys (this volume).

knowledge more reliably (Andringa, 2020; Granena, 2013; Suzuki, 2017). Morgan-Short and colleagues (e.g., Morgan-Short et al., 2011) have investigated the extent to which EEG can be used to disentangle the two knowledge types, while Rebuschat and colleagues (e.g., Hamrick & Rebuschat, 2012; Grey et al., 2014; Rebuschat & Williams, 2012b; Tagarelli et al., 2016) have relied on the use of subjective measures of awareness. An important recent trend is the triangulation of measures of awareness, i.e., the comparison of multiple awareness measures within the same study to determine what each can and cannot contribute (Godfroid & Schmidtke, 2013; Rebuschat et al., 2015).

Potential Directions for Cross-Disciplinary Exploration

In the previous section, we compared three research strands that are directly relevant to our understanding of implicit and explicit learning of language. This comparison across several research dimensions should enable us to better understand what each of these strands can contribute to the bigger picture. For example, implicit learning has placed the cognitive unconscious back at the heart of research on language learning, and it has promoted experimental tasks and paradigms that allow us to distinguish the contributions of implicit and explicit processes in language learning. In return, 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 essential proof of concept for the potential role of implicit learning in language acquisition. Finally, experimental SLA studies using natural languages complement implicit learning and statistical learning studies that rely on finite-state grammars or other artificial systems, and they also provide us with an applied perspective that is often missing in the more fundamental research conducted within implicit learning and statistical learning. I would like to conclude this chapter by highlighting themes that would particularly benefit from further cross-fertilization across strands (Reber, 2011).

Individual Differences in Implicit Learning

Early research suggested that individual differences might play a more minor role in implicit learning than they do in explicit learning, so this area has traditionally received very little attention (Reber, 1993). This view has changed considerably in recent years, with an increasing number of studies observing substantial variation across participants completing standard implicit and statistical learning tasks (e.g., Kalra et al., 2019; Kaufman et al., 2010; see Allen, this volume, for discussion). This has raised intriguing questions about implicit aptitude (Godfroid & Kim, 2021; Granena, 2020; Suzuki, 2021) and statistical learning as an ability (Arnon, 2019; Siegelman et al., 2017). For example, if implicit learning is an ability, does it improve during development, potentially even in adulthood, or is this fully developed in childhood (Howard & Howard, this volume)? How reliably does performance on implicit or statistical learning tasks predict variation in (natural) language learning outcomes? There is now substantial evidence linking performance on statistical learning measures and real-world language outcomes, including speech perception, sentence processing, L2 literacy, and vocabulary size (Siegelman, 2020), but the relationship is more complex than anticipated and awaits further investigation. Importantly, we also need to understand how this ability relates to other individual difference variables that have been shown to affect learning rate and ultimate attainment in child and adult language acquisition. Here, we need to understand how implicit or statistical learning ability, as measured by performance on standard tasks (AGL, SRT, ASL, CSL, etc.), relates to other, potentially overlapping cognitive constructs such as working memory, declarative memory, and procedural memory (Hamrick et al., 2018; Pili-Moss et al., 2020; Walker et al., 2020) and widely used language learning aptitude measures (MLAT: Carroll & Sapon, 1959; Hi-LAB: Linck et al., 2013; LLAMA: Meara, 2005). In addition, we also need to understand how implicit or statistical learning ability relates to other key determinants of success in language learning, including age of acquisition, length of exposure, previously acquired languages (simultaneous and successive bilingualism, L3 acquisition, etc.), and motivation.

The Implicit–Explicit Interface

From an applied perspective, the question about what can and cannot be learned implicitly is of great interest, as those language features that cannot readily be acquired implicitly are obvious targets for more explicit interventions (e.g., in the context of foreign language instruction). The interaction of implicit and explicit processes has been systematically explored in implicit learning research (Reber, 1993) and especially in SLA research, where this issue is usually referred to as the implicit-explicit interface. R. Ellis (2005, p. 143) summarizes the situation as follows: "There is broad consensus that the acquisition of an L2 entails the development of implicit knowledge. However, there is no consensus on how this is achieved; nor is there consensus on the role played by explicit knowledge." Several important questions have been addressed over the past two decades, though not necessarily fully answered (see Godfroid, in press, for review). For example, it is still debated what language features are best acquired via implicit learning and which features would benefit from explicit instruction. Do we require implicit or explicit learning for simple or complex language structures, for frequent or infrequent ones, for items that are low or high in salience? In terms of intervention, we need to better understand what types of explicit treatments are most effective in promoting learning (e.g., rule search, metalinguistic rule presentation, explicit feedback, see Monaghan et al., 2019, 2021), when we should provide explicit treatments (before, during, or after implicit training), and, importantly, how explicit treatments interact with more implicit ones. Further, we need to understand how the effectiveness of implicit and explicit instruction is mediated by individual difference variables. Why is it, for example, that some learners become aware of the (hidden) learning target during implicit training while others do not? (Andringa, 2020; Monaghan et al., 2019) Many factors could lie behind this development of insight, including working memory capacity, age, and previously acquired languages. Also, it's clear that some learners benefit more from explicit treatments than others. Again, why should this be the case? Studies suggest that the answer to these questions is complex, and I suspect that the answer ultimately depends on an interplay of several factors, including (1) individual learner characteristics (e.g., distribution of attentional resources, Hsiao & Reber, 1998; Reber et al., 1980), (2) training task and exposure condition (implicit vs. explicit, form-focused vs. meaning-focused), and (3) nature of linguistic learning target (phonology, vocabulary, morphology, syntax; complexity of target structures, see DeKeyser, 2005). A more comprehensive answer to the interface question might well require a concerted effort across research groups and large-scale data sets.

Methodological Alignment

Significant progress on topics such as these is likely to require greater methodological alignment across the three strands. Each community will continue to develop training tasks and novel measures of learning, but once these measures have been psychometrically validated (R. Ellis, 2005; Siegelman et al., 2016), they should be more widely shared, not just within our own communities, which is the standard, but also across research communities.[2] This way, findings of artificial and natural language studies could be compared more easily. This type of cross-disciplinary interaction has already begun, which is a very promising development. Good examples are Suzuki and DeKeyser's (2015) use of Kaufman et al.'s (2010) reaction-time task, Godfroid and Kim's (2021) use of the ASL and

[2] This could be done, for example, via the IRIS Digital Repository (https://www.iris-database.org/) or the OSF platform (https://osf.io/).

VSL task validated by Siegelman et al. (2017), or Batterink et al.'s (2014) use of the artificial stimuli developed by Williams (2005).

In addition to sharing validated tasks, more research is needed on the relationship between different tasks. This includes more research on the fundamental link between artificial language learning and the acquisition of natural languages (Arnon, 2019; Ettlinger et al., 2016; Robinson, 2005) as well as the systematic exploration of the relationship between different types of tasks that are widely used across the three strands (Godfroid & Kim, 2021; Granena, 2013; Suzuki & DeKeyser, 2017). For example, Godfroid and Kim (2021) used structural equation modeling to investigate the relationship between standard implicit and statistical learning tasks (ASRT, ASL, VSL, etc.) and tasks that measure implicit and explicit knowledge of language (word monitoring, self-paced reading, elicited imitation, grammaticality judgments, etc.). These types of methodological studies are particularly valuable and should facilitate the use of similar tasks across strands. This methodological alignment would, in turn, facilitate comparison of results across studies.

Methodological Syntheses

Finally, there is clearly a need for methodological syntheses. SLA is a field blessed with meta-analyses—between 1996 and 2010 alone, 27 meta-analyses were published or in press (Oswald & Plonsky, 2010)—and many of these are immediately relevant to the study of implicit and explicit (second) language learning (see Goo et al., 2015; Kang et al., 2018; Norris & Ortega, 2000; Sok et al., 2019; Spada & Tomita, 2010). Meta-analyses such as these greatly contributed to the methodological refinement of experimental SLA research, yet similar publications are rare in implicit or statistical learning research (see Frost et al., 2019, and Siegelman et al., 2016, for exceptions). It would be of great value to have similar analyses for these areas, too, and more importantly, to have syntheses that compare methodological design choices across the three strands.

Conclusion

Over the past decades, studies from different research areas, including (but not limited to) the three strands discussed above, have examined the acquisition of simple and complex linguistic features via distributional learning, under incidental exposure conditions and across a range of populations, from infants and children to younger and older adults. This research is fundamental, as it directly addresses questions about the potential contributions of implicit and statistical learning in language acquisition across the lifespan, and substantial progress has been made (Frost et al., 2019; Saffran & Kirkham, 2018; Williams, 2020). When engaging with the literature in these strands, it is often striking how much overlap there is in terms of research questions and priorities. Often, the same questions have been addressed, but with different research paradigms or populations, thus providing important complementary evidence that would be of great value to other strands. Yet, this makes it all the more surprising (and perhaps a bit frustrating) that there should be still so little interaction across strands. As Frost et al. (2019) point out, this insularity applies to all research strands and results from historical divisions of research communities into fixed research areas. However, if we are to arrive at integrated theories of implicit and explicit learning of languages, we cannot afford to focus so heavily on our respective strands, with their preferred publication venues, conferences, research themes, and paradigms, that we end up accidentally disregarding important data provided by other communities. I hope the present chapter facilitates this interaction by pointing readers to exciting research that they might have been unaware of and that might benefit their future studies.

Acknowledgments

I am grateful to Arthur Reber and Rhianon Allen for their helpful comments on an earlier version of this chapter and for providing me with a unique opportunity to connect with research domains outside my area of expertise (language). Reading the chapters in this volume, it was interesting to see that the same topics, theoretical debates, and methodological challenges occur across very distinct disciplines and research domains. This is perhaps unsurprising, given that all chapters focus on facets of the cognitive unconscious, but it also serves as an inspiring reminder that we stand to benefit immensely from engaging (at least occasionally) with other research domains and literatures.

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