New Directions in the Study of Implicit and Explicit Learning: An Introduction

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It has been exactly 10 years since Studies in Second Language Acquisition published a thematic issue on the topic of implicit and explicit second language (L2) learning, edited by Jan Hulstijn and Rod Ellis (2005). This seminal issue consisted of a brief general introduction (Hulstijn, 2005), five experimental studies (R. Ellis, 2005; de Jong, 2005; Robinson, 2005; Tokowicz & MacWhinney, 2005; Williams, 2005), and a review article on the implicit-explicit interface (N. C. Ellis, 2005). The current issue similarly takes stock of recent developments in implicit and explicit language learning research. In this introduction, we will redefine the notions of implicit and explicit learning, briefly sketch the new directions this field of inquiry has ventured into, and illustrate how the contributions to this thematic issue exemplify recent trends and developments.

In his introduction to the 2005 thematic issue, Hulstijn (2005) identified implicit and explicit learning as one of the more urgent matters to be addressed by L2 researchers. This is still true, and one could even argue that the topic has gained in relevance, because it started to engage more with other issues in the field of SLA, a point we will return to later. In the field of SLA, interest in the topic can be traced back to Krashen’s (1977, 1979, 1981, 1994) proposals, according to which L2 development relies primarily on language acquisition (i.e., an incidental process that results in implicit [unconscious] linguistic knowledge), with little role for explicit knowledge or processes. We will not revisit these discussions in detail here, but it is important to establish that the distinctions between implicit and explicit knowledge and learning are widely accepted within the field of SLA.

At the most fundamental level, the explicit-implicit distinction is about whether learning in the absence of awareness is a real possibility; however, the implications are much wider. The
distinction between implicit and explicit learning and knowledge and how they interface is crucial for a proper understanding of how L2 proficiency develops, as has been forcefully argued by many (e.g., N. C. Ellis, 2015; R. Ellis, 2005; Hulstijn, 2015). The distinctions are needed to understand language learning trajectories and the extent to which these are or can be uniquely shaped by implicit learning processes; to understand differences between child and adult L2 acquisition; to understand which features of the L2 are amenable to explicit instruction and to what extent this amenability interacts with individual characteristics such as one’s first language (L1) or language-related cognitive capacities; and to understand differences between learning in different contexts of learning. In other words, the explicit-implicit distinction permeates into just about every major theme in the study of SLA.

Three empirical questions have already resulted in a substantial amount of research (see also Rebuschat, 2015). The first question concerns the role of awareness in L2 acquisition and the possibility of learning without awareness (e.g., Hama & Leow, 2010; Leow, 1997, 2000; Leow & Hama, 2013; Leung & Williams, 2011; Rebuschat, Hamrick, Sachs, Riestenberg, & Ziegler, this issue; Schmidt, 1990, 1995a, 1995b, 2001; Williams, 2005, 2009). The second question is methodological and concerns the process of measuring awareness. Most research has concentrated either on the question of how to measure awareness at the time of encoding (i.e., while participants are engaged on a learning task) or on the question of how to measure awareness of what has been learned (i.e., of the product of learning; e.g., R. Ellis, 2005; Godfroid, Loewen, Jung, Park, Gass, & Ellis, this issue; Grey, Williams, & Rebuschat, 2014; Hamrick & Rebuschat, 2012; Leow, 1997; Leow, Grey, Marijuan, & Moorman, 2014; Rebuschat, 2013; Rebuschat et al., this issue). The third question focuses on the implicit-explicit interface (i.e., the issue of whether explicit knowledge can foster the development of implicit L2
knowledge; Andringa & Curcic, this issue; Cintrón-Valentín & Ellis, this issue; N. C. Ellis, 2005).

Redefining Implicit and Explicit Learning

In his widely-cited introduction to the 2005 issue, Hulstijn conveniently provided definitions for implicit and explicit memory, implicit and explicit knowledge, implicit and explicit learning, as well as implicit and explicit instruction. In each pair, the absence or presence of conscious awareness decides between the implicit or explicit status of the construct. He also defined inductive and deductive learning as types of explicit learning and incidental and intentional learning as relatively distinct modes of learning that are related but separate from implicit and explicit learning. There is little need to revise these definitions, with the exception perhaps of the definitions that Hulstijn provided for implicit and explicit learning, which he already identified to be the most controversial, because one’s conceptualization of implicit and explicit learning is largely determined by the views one espouses on how language is represented in our minds (symbolic or subsymbolic). In Hulstijn’s (2005) words, “…definitions of learning—whether implicit or explicit—as a process (how) can easily become contaminated with the object of learning (what)” (p. 133). This is how Hulstijn defined explicit and implicit learning:

Explicit learning is input processing with the conscious intention to find out whether the input information contains regularities and, if so, to work out the concepts and rules with which these regularities can be captured. Implicit learning is input processing without such an intention, taking place unconsciously. (p. 131)

On close examination, these definitions do not say much about the actual learning mechanisms themselves. They state that learning is input processing without conscious awareness, but the exact nature of such input processing remains unclear. Hulstijn defined
explicit learning mainly in terms of what is learned and his use of the term regularities in this definition seems to limit the construct of explicit learning to those aspects of language that are regular. Because implicit learning was defined as the inverse of explicit learning (that is, in negative terms, as input processing without the conscious intention to learn the regularities of the language), the same holds for implicit learning. Although it is true that most thinking and research has been devoted to the acquisition of the rules of the L2, neither types of learning are limited to the learning of regularities, and it seems more accurate to say that both regular and irregular phenomena can be learned explicitly and implicitly. Learners can explicitly learn the exceptions to a rule, and they can learn to behave according to these exceptions without being consciously aware of them.

For both implicit and explicit learning, it is still difficult to define the constructs more carefully in terms of the how. If learning is input processing, then what are the exact processes involved? The contributions to this issue bear testimony to the fact that progress is being made in this area. For example, both L1 and L2 acquisition researchers have increasingly turned to the concept of statistical learning as the primary language learning mechanism, as testified by Caldwell-Harris, Lancaster, Ladd, Dediu, and Christiansen (this issue) and a recently published edited volume on statistical learning in L1 and L2 acquisition (Rebuschat & Williams, 2012b). It is useful to explore briefly this concept and how it is related to implicit and explicit learning. Statistical learning holds that language learning results from our sensitivity to the distributional properties of the input. Humans (and other mammals) are extremely well-attuned to frequencies of occurrence and co-occurrence. Statistical learning is generally considered to be a domain-general mechanism (i.e., not specific to language; Rebuschat & Williams, 2012a), although some argue that it operates under language-specific constraints (e.g., Shukla, Gervain, Mehler, &
A hallmark property of statistical learning seems to be that it occurs unconsciously and unstoppably when humans are exposed to (linguistic) input. Some equate statistical and implicit learning without further ado (e.g., Conway, Bauernschmidt, Huang, & Pisoni, 2010; Kuhn & Dienes, 2008), and others even go as far as combining the two in name, as in *implicit-statistical learning* (Conway & Christiansen, 2006; Onnis, Destrebecqz, Christiansen, Chater, & Cleeremans, 2015; Perruchet & Pacton, 2006; Perruchet & Poulin-Charronat, 2015; Walk & Conway, 2015).

Statistical learning, then, refers to a gradual process of accumulating linguistic knowledge based on the distributional properties of the input. Grammatical structure emerges in the course of extended periods of time and many exposures to the target structure (Bybee, 2008; N. C. Ellis, 2008; N. C. Ellis & Larsen-Freeman, 2006; N. C. Ellis & O’Donnell, 2012). Such a gradual learning process is somewhat at odds with the fleeting concepts of attention to form and possible awareness of that form, which are associated with brief and distinct points in time (Doughty, 2001; Robinson, 2003). This potential mismatch in temporal granularity between implicit, statistical learning processes and attention and awareness may make it difficult to become consciously aware of the more abstract generalizations that result from such learning, especially in natural language learning contexts. If implicit learning is indeed, in essence, a statistical learning process, then what does that mean for explicit learning? Could the same statistically driven input processing mechanisms lie at the heart of both implicit and explicit learning, the only difference being the level of awareness at which implicit and explicit learning operate?

Explicit learning is generally defined as learning to think and talk about the language system in symbolic terms, in terms of rules and their exceptions, by committing these to memory practice and rehearsal (N. C. Ellis, 2015; R. Ellis, 2004, 2005; Hulstijn, 2005). Several
researchers have pointed to the fact that the output of explicit and implicit learning processes is highly different in nature and therefore difficult to align: “…it is not easy to see how knowledge as weighted content (i.e., as a set of neural pathways of greater or lesser strength) can be anything other than separate from knowledge of linguistic facts” (R. Ellis, 2004, p. 234). However, the ultimate goal of explicit learning is not simply knowledge of concepts and rules. Explicit instruction is mostly provided to help learners process the input in ways that are thought to be conducive to the L2 acquisition process, a notion that is central to processing instruction approaches (VanPatten & Cadierno, 1993; VanPatten, 2006).

If the interface debate is considered from a statistical learning perspective, then the question becomes: To what extent can statistical learning processes be influenced by explicit instruction and metalinguistic information? Nick Ellis has argued that instruction may serve to direct attentional processes towards particular formal aspects of the input and away from others, which in turn affects the frequency-based uptake of these forms (N. C. Ellis, 2002, 2005, 2015; N. C. Ellis et al., 2014). Cintrón-Valentín and Ellis (this issue) is a direct test of this possibility. The study demonstrates how form-focused instruction may cause certain cues in the input to be blocked from attentional processes, which in turn affects how well those cues are learned. However, explicit instruction and learning can also be seen an attempt to somehow “hardwire” associations and processing routines that are normally the outcome of a gradual, statistical learning process. Andringa and Curcic (this issue) is a test of the possibility that explicit information can be a shortcut to input processing in more targetlike ways and, consequently, a circumvention of statistical learning processes. As such, the study is a test of the strong version of the interface hypothesis that claims that explicit knowledge directly affects implicit knowledge. However, their results do not warrant any firm conclusions about such an interface.
Online Processing and Implicit and Explicit Learning

The use of new measurement techniques illustrates how the field is seeking to better understand the input processing mechanisms underlying implicit and explicit learning and knowledge. This issue clearly reflects this. Morgan-Short, Deng, Brill-Schuetz, Faretta-Stutenberg, Wong, and Wong (this issue) used functional magnetic resonance imaging (fMRI) to study the neuro-physiological properties of syntactic processing after implicit instruction; Cintrón-Valentín and Ellis (this issue) used eye-tracking to investigate attention to form during reading to find evidence of blocking (i.e., absence of attention to particular forms due to instruction); Godfroid et al. (this issue) also used eye-tracking during reading to study attention to form in timed and untimed grammaticality judgment tasks to find evidence of more controlled language processing in untimed grammaticality judgment tasks; and Andringa and Curcic (this issue) used a visual world eye-tracking paradigm to assess learners’ ability to predict upcoming linguistic input as a result of explicit instruction.

Interestingly, although each of these studies looks at online input processing mechanisms, they all zoom in on different aspects of input processing. This is a demonstration of the fact that input processing is a complex, multicomponential construct. For each of these techniques, it is necessary and interesting to think about what processes exactly are isolated and how these are related to or unique to implicit and explicit learning or the engagement of implicit and explicit knowledge. Both Godfroid and Winke (2015) and Morgan-Short, Faretta-Stutenberg, and Bartlet-Hsu (2015) provide excellent discussions of the kinds of processes that can be measured with eye-movement and event-related potential (ERP) techniques, respectively. The thing to be learned from these discussions is that there is no one-to-one relationship between the processes that these techniques tap into and implicit and explicit processing and learning. At the same time,
it is important to construct hypotheses about such relationships. Work presented in this issue, for example, hypothesizes that retrospective processes may be evidence of the involvement of explicit knowledge—a possibility explored by Godfroid et al. (this issue). Andringa and Curcic (this issue), on the other hand, labor from the assumption that predictive processes are based in implicit processes.

**Measurement Issues**

A continual concern in the study of implicit and explicit learning research is measurement. One of the thorny issues in particular is the search for measures that can assess whether knowledge of a particular structure is either implicit or explicit. Pure measures of implicit and explicit knowledge are of crucial importance if one wants to falsify the hypothesis that learning without awareness is impossible (Reber, 1989; Williams, 2005). It has been difficult to establish that learning can occur without awareness, simply because our designs and measures do not preclude the possibility that at some point in the learning process some level of awareness occurred for the target structure (cf. DeKeyser, 2003). At the same time, it is certainly true that learning has been shown to occur in situations that did not allow for much conscious processing of the target structures. Much of the debate in this line of research centers on the validity of the measures used to ascertain absence of awareness (Hama & Leow, 2010; Leow, 2000; Rebuschat, 2013; Williams, 2005). Similarly, many have stressed the urgent need for tests that can measure implicit and explicit knowledge separately to settle questions about a potentially facilitative role that explicit knowledge can play in the acquisition of implicit knowledge (Andringa, de Glopper, & Hacquebord, 2011; Han & Ellis, 1998; R. Ellis, 2004, 2005). It is a well-established fact that tasks bias towards the use of one or another type of knowledge, and most studies have used measures favoring explicit knowledge (Doughty, 2003; Norris & Ortega, 2000).
In this issue, both Rebuschat et al. and Godfroid et al. explicitly address such measurement concerns. Rebuschat et al. concurrently administered three measures that have been used often to assess the possibility that learning took place without awareness. One of the interesting findings of the study is that it provides evidence for the idea that the measures themselves affect learning outcomes. Particular tasks appeared to trigger participants to look for rules that they had not yet noticed or realized might be present in input; in addition, particular task features were found to interfere with the ability to generalize patterns to new contexts. Godfroid et al. (this issue) compared reading behavior in timed and untimed grammaticality judgments to confirm earlier findings that these tasks measure separate kinds of linguistic knowledge (Bowles, 2011; Han & Ellis, 1998; R. Ellis, 2005).

Findings such as these emphasize the importance of task design and of research into how properties of testing tasks may bias participants towards the use of a particular type of knowledge, which has large repercussions for the interpretation of the findings based on such tasks. As already touched upon, reviews and meta-analyses into the effects of instruction have revealed strong biases in instruction studies towards the use of tasks and testing procedures that favor the use of explicit knowledge over implicit knowledge (R. Ellis, 2002; Norris & Ortega, 2000; Spada & Tomita, 2010). It is interesting to note, in this respect, that the online measurement techniques that are being introduced in the field, most notably ERP and fMRI techniques, reveal a similar bias. They rely on task procedures and test circumstances that are favorable to the application of explicit knowledge and are more likely to generate awareness of the target structure (through the provision of generous amounts of response time, the use of ungrammatical items, and perhaps also the absence of fillers). Only the visual world eye-tracking technique (exemplified by Andringa & Curcic, this issue) avoids these task features all together,
but the technique is applicable to a limited set of language phenomena only. All this underscores Godfroid and Winke’s (2015) and Morgan-Short et al.’s (2015) contention that there is no one-to-one relationship between online measures and implicit processing. In the interpretation of results obtained from online measures, it is important to consider the implications of task design.

New Lines of Inquiry

This issue demonstrates how questions of implicit and explicit learning have started to engage more with other themes in the study of L2 acquisition. As Paciorek and Williams (this issue) point out, implicit and explicit learning studies are not solely about whether learning can be entirely implicit. Their relevance also lies in their potential to increase our understanding of how input is processed and how tasks affect either type of learning. However, by applying questions of implicit and explicit learning to ever more varied linguistic phenomena and learning contexts, knowledge is gained about what can or cannot be learned implicitly and for whom such learning is or is not attainable. A case in point is Caldwell-Harris et al. (this issue), who investigated the acquisition of tonal features of language and found clear differences between learners from languages that possess tonal distinctions and learners from language backgrounds that lack these distinctions. Paciorek and Williams (this issue) also illustrate this point nicely: Their study is one in a line of studies that together serve to investigate the limits of implicit learning (e.g., Chen et al., 2011; Leung & Williams, 2011, 2012; Williams, 2005). For the present issue, they assess learners’ ability to implicitly acquire the collocational preferences of novel verbs and provide evidence that this is a feature that can be learned implicitly.

Finally, there appears to be an increasing recognition of the idea that individuals may differ in their ability to learn either explicitly or implicitly. In psychology, both implicit learning ability and statistical learning ability have been considered by most to be fairly stable constructs
both in terms of variation between individuals and within individuals over time (Misyak, Goldstein, & Christiansen, 2012). Similarly, when Krashen proposed his theory of L2 acquisition, he proposed a stable language acquisition device for implicit acquisition and attributed individual differences and age effects to differences in the ability to use explicit knowledge as a monitor and to the affective filter (e.g., Krashen, 1981). In the field of SLA, there has been much recognition for the existence of individual differences in language learning ability through aptitude research, but the measures most commonly used in aptitude research have been criticized for not tapping into differences in implicit learning ability. It is fair to say that research into individual differences in implicit learning ability is in its infancy. Both Caldwell-Harris et al. (this issue) and Morgan-Short et al. (this issue) address individual differences: Caldwell-Harris et al. show that L1 background affects statistical learning processes, whereas Morgan-Short et al. were able to establish links between the recruitment of particular neural circuits and performance on behavioral measures of declarative and procedural memory.
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