Implicit Learning: History & Applications

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Abstract

The history of research on implicit learning has been driven primarily by studies using specialized laboratory tasks that are designed to isolate our ability to extract statistical structure from experience, outside of awareness of what is learned. This empirical approach has been fruitful and necessary to establish implicit learning phenomena. It has allowed for systematic characterization of the mechanisms and neural systems that are the basis of this type of memory. However, the question of how pervasive implicit learning is in our everyday human experience is not directly addressed by this laboratory-based approach. The fact that implicit learning does not leave a conscious memory trace runs the risk of it being overlooked as an important component of complex cognition. Here, applications of implicit learning in three established research domains are briefly reviewed as examples of phenomena that appear to be driven by knowledge outside of consciousness. This review will show how this type of memory plays important roles in domains as diverse as language learning, skill acquisition and decision making processes. The principles extracted from implicit learning research can provide important theoretical contributions to these other domains and points towards the importance of examining relatively unexplored questions about the nature and processes involved in interactions between memory systems in complex cognitive processing.

Introduction & History

The term “implicit learning” was first published 50 years old in a report titled, “Implicit Learning of Artificial Grammars” (A.S. Reber, 1967). This paper described studies with a novel paradigm aimed to create a laboratory analogue of language learning. The new approach was based on using mathematical formalisms for stimulus creation that were similar to ones being developed to help understand human language function. Surprisingly, participants exhibited an unusual behavioral pattern in their learning process. They appeared to be learning to be sensitive to the statistical structure of the underlying formalism, but seemingly without any awareness that there were any underlying rules. This report established the possibility of a dissociation between learning that could only exhibited through performance and more traditional learning and memory that was available to conscious awareness. Over the next several decades a wide variety of additional studies and many more novel paradigms were constructed to drive research into understanding the phenomenon of implicit learning (A.S. Reber, 1989; P.J. Reber, 2013).

The historical context in which the original report was published provides some insight into why this finding had such a widespread, enduring impact and how the idea of implicit learning came to be foundational to the modern characterization of Memory Systems Theory (Squire, 1992) and the cognitive neuroscience of memory. The story of the basis of the original studies (A.S. Reber, personal communication) starts with a chance meeting between the author, Arthur S. Reber, and George A. Miller in the early 1960s. Miller had fairly recently published the seminal paper on “the magic number 7” and working memory (Miller, 1956) which is often cited as one of the core reports demarking the shift in the field of Psychology away from Behaviorism and to Cognitive Psychology, known as the Cognitive Revolution. Other notable publications also considered in the same vein include Broadbent (1958), Newell, Shaw & Simon (1958) and a review written by Chomsky (1959) highly critical of a book by B.F. Skinner (1957) titled “Verbal Behavior.”

The Cognitive Revolution was effectively a movement against and away from the Behaviorist school that had attempted to put Psychology on robust scientific footing through the use of simple, well-characterized task with quantifiable measures that allowed for robust, reliable experimental paradigms. In practice, this meant using tasks from the tradition of physiologists (e.g., Pavlov’s conditioning research) that could also be studied in animal models. However, the extrapolation from animal cognition to human cognition has always posed some difficult questions, in particular when considering complex human cognition and especially the process of language, which is effectively unique to humans. Skinner’s suggestion (1957) that language could be explained from reinforcement and conditioning studies was forcefully rejected by Chomsky (1959), implying that the study of human cognition needed a different approach.

The new approach favored by Chomsky led to his seminal work developing the field of computational linguistics. Early explorations of this work appeared in the Handbook of Mathematical Psychology (1963; ed. R.D. Luce) which includes three chapters authored or co-authored by Chomsky outlining how language production and comprehension might be modeled with formal grammars. Two of these chapters were co-authored with Miller, which provides some context for how Reber, as a graduate student at nearby Brown University, came into contact these formalisms through Miller (at Harvard) via their occasional interactions.

While Chomsky's research program can be seen as characterizing mathematical formalisms that would account for human language production and comprehension, Miller and Reber were considering a separate but related problem. If these grammars were how humans accomplished language, how does a human acquire them? The formalisms seemingly required to account for language use appeared to be exceedingly complex and possibly entirely unlearnable, especially considering the cognitive abilities of newborns. One approach was to assume they were not learned, necessitating the existence of a pre-wired "universal grammar" embedded in the human brain (e.g., genetically endowed). Another approach was to try to capture this learning process in the laboratory using simplified 'artificial grammars,' which then led to the seminal finding (A.S. Reber, 1967) and observation of a novel type of human learning that might solve this 'unlearnability' problem for language.

Researchers familiar with this history are aware that the idea of implicit learning did not immediately revolutionize the study of memory or language. In fact, for much of the next several decades, there followed a great deal of debate centered on the difficult problem of establishing the 'implicit' part of this kind of learning. With a definition of implicit learning founded on 'not available to consciousness,' establishing even the existence of this phenomenon depends critically on proving a universal null, no awareness, which is an essentially intractable problem (Merikle, 1994). While experimental techniques and measurement approaches eventually began to provide guidelines for tackling this issue(Dienes & Berry, 1997), important support for the concept also emerged from ideas being developed separately and in parallel from research in neuropsychology and neuroscience.

Cognitive Neuropsychology and Systems Neuroscience

At around the same time as the several famous publications in cognitive psychology that launched the Cognitive Revolution were published, a landmark paper in human cognitive neuropsychology was also reported. Scoville & Milner (1957) described the famous case of the patient H.M., who exhibited severe and selective impairment to his ability to acquire new conscious memories after bilateral medial temporal lobe (MTL) removal to treat otherwise intractable epilepsy. While there had been a few prior reports of selective cognitive loss following localized brain regions (Broca, Wernicke) the theoretical model of the time was dominated by Lashley's (1929) theory of equipotentiality that hypothesized that any region of the brain could support high-level cognitive function. The case of patient H.M. established that memory was dependent on a specific neural region and did not arise from mass action of neural changes across the entire brain.

Research over the next 35 years characterized the structure and function of the memory circuitry within the MTL (hippocampus and adjacent cortical areas) and established that this system was critical for the acquisition and consolidation of memories for facts and event (Squire, 1992). Patients with damage similar to H.M. are unable to acquire new explicit memories, but are able to retrieve remote episodic memories of events that occurred prior to the damage to the MTL. More recent memories are partially affected by a temporal gradient of retrograde amnesia (see Lechner et al., 1999, for a review and history), leading to the development of a theory of memory consolidation dependent on a gradual process of memory strengthening and reorganization that depends on the MTL after initial learning.

However, detailed neuropsychological assessment of H.M.'s memory capabilities subsequently indicated that not all learning processes in his brain were entirely disrupted. Corkin (1968) and Milner, Corkin, Teuber (1968) documented improvements in performance in procedural tasks (mirror tracing), maze learning, and picture identification from fragments. Shortly after, Weiskrantz & Warrington (1970) described a broader phenomenon of intact memory from fragmentary information in amnesic patients (priming) that would come to be known as "implicit memory" and very widely studied (Schacter, 1987). Together these findings indicated that another type of memory existed that did not operate in the same manner as memory for new facts and events that depended on the MTL memory system.

These findings were foundational to the development of a 'memory systems framework' that aimed to connect these observations about human memory to research going on in parallel on the neuroscience of memory. The field of neuroscience also progressed remarkably over the course of the 20th century (c.f. Gross 1999 for a highly readble overview) with a notable moment in this progression being the founding of the Society for Neuroscience in 1969. With respect to specifically the neurobiology of learning and memory, an important early paper was the work of Kandel & Spencer (1968), who began to characterize the underlying biology of synaptic change in the nervous system. It is of note that all three of these then independent lines of research on learning and memory saw significant results in a similar time frame in the second half of the 1960s. However, integration of the related ideas across these research areas did not emerge until somewhat later during the development of the interdisciplinary field of Cognitive Neuroscience.

A great deal of neuroscientific memory research through the subsequent years was focused on establishing and characterizing the role of the MTL in explicit, declarative memory (facts and events). While observations from patients such as H.M. were fascinating, it was understood that it would require the establishment of a model system to be able to characterize how MTL damage affected memory with experimental control. The roles of the hippocampal formation, the adjacent cortical areas (entorhinal, perirhinal, parahippocampal) and the amygdala were all studied in detail (Squire, 1992). Systems-level analysis eventually converged on the key importance of the hippocampus and the adjacent cortical areas with the amygdala playing largely a modulatory role related to emotional memory. In addition, examination of the phenomenon of retrograde amnesia following MTL damage led to the characterisation of memory consolidation processes as a key feature for how the MTL operates to store information.

Evidence for consolidation theory was also accumulating in parallel in research on the neurobiology of synaptic change (McGaugh, 2000). Synergy across these areas demonstrated how cellular and systems neuroscience could inform each other in building a theory of memory (Milner, Squire, Kandel, 1998). Connections to research on psychological phenomena directed at studies of complex cognition were not immediately evident. Animal models do not allow for research on processes related to language or subjective measures of consciousness. Instead, many of the paradigms used to characterize and quantify learning and memory processes in these animal model systems were closely related to the tasks developed by the Behaviorist researchers (e.g, conditioning models of learning) which were very well suited to neuroscientific study of learning and memory.

Implicit learning and the problem of assessing awareness

Studies of implicit learning through two decades following the original description of the AGL task aimed to better characterize this kind of learning (A.S. Reber, 1989) but struggled with the question of how to firmly establish when learning was outside awareness. Assessing a lack of awareness depends on an accurate model of the information learned by participants to guide assessments of conscious knowledge. Dulany, Carlson & Dewey (1984) and Perruchet & Pacteau (1990) found that asking participants about the letter strings used in the AGL paradigm specifically elicited some additional knowledge related to determining whether the strings followed the grammar rules or did not. This raised the possibility that participants were inferring another type of representation that allowed them to make 'grammaticality' judgments without being aware of the specifics of the formal grammar. However, it was also possible that these assessments were not of the awareness of the knowledge that drove the grammaticality judgment, but reflected concomitant explicit memory for the study stimuli (which would naturally be acquired by cognitively healthy participants but might not contribute to AGL performance).

Similar questions were being raised about studies of implicit memory (e.g., Roediger, 1990)**.** To show that this type of memory did not depend on explicit memory for previously seen stimuli, it would be necessary to show robust priming in the absence of conscious memory. In cognitively healthy participants, this proved to be extremely difficult as a participant with an intact MTL memory system will always have some explicit memory of the study items. The inability to show a strong dissociation made it impossible to rule out the hypothesis that implicit memory phenomena simply reflected a weaker form of explicit memory (similar to familiarity) rather than a separate form of memory entirely.

A new paradigm for studying implicit learning was described by Nissen & Bullemer (1987), the Serial Reaction Time (SRT) task that became quite widely popular. This task embedded a covert repeating sequence into a simple choice reaction time task. Participants were found to increase their speed of responding to a practiced sequence compared with unpracticed sequences without seemingly being aware of the repetitions. In addition to the dissociation with awareness, this paradigm was also shown to exhibit intact learning in memory-impaired patients (Korsakoff's) in the original report. Like with the AGL paradigm, concerns emerged over the content of the representation (Reed & Johnson,1994) which led to protocol improvements without changing the basic character of the finding. However, the development of increasingly sensitive measures of explicit sequence knowledge (Perruchet & Amorim, 1992; Willingham, Greeley & Bardone, 1993) started to show the same pattern observed in other tasks used in implicit memory research. Participants with intact explicit memory tended to have at least some memory for the covertly embedded (implicit) information, even if it was not clear that it contributed to task performance.

Memory Systems Theory

The emergence of an integrated memory systems theory that used an interdisciplinary Cognitive Neuroscience approach eventually showed how the neural basis of memory function in the brain could be used to help understand the type of learning observed in implicit learning paradigms. Squire (1992) described a taxonomy of memory types within a single major subdivision based on the importance of the MTL memory system. Declarative memory referred to information that required the MTL memory system to store (and consolidate) and produced representations that were generally available to awareness and verbal report. Nondeclarative memory described a collection of other phenomena that did not depend on the MTL memory system but were instead supported by synaptic change in other circuits.

Applying this framework to phenomena of implicit learning, Knowlton, Ramus & Squire (1992), and Knowlton & Squire (1996) showed that as predicted, AGL was intact in patients with severely impaired memory due to MTL damage. P.J. Reber & Squire (1994; 1998) established the same parallel finding for the SRT task with techniques in protocol design and awareness assessment that had been advanced since Nissen & Bullemer (1987). Research on implicit memory with particularly severely memory-impaired patients indicated that it was possible to observe intact priming in the complete absence of explicit (declarative) memory for stimuli (Hamann & Squire, 1997; Stark & Squire, 2000). In each case, the tasks studied with cognitively healthy participants as implicit learning, lined up well with neuropsychological studies that showed an important role for nondeclarative memory. P.J. Reber (2013) reviewed these areas and described a general framework for memory based on the MTL memory system together with general, pervasive neuroplasticity mechanisms that shape processing everywhere else in the brain to adaptively improve functioning via practice (repetition).

This framework provides a neurocognitive foundation for studies of memory that depend on implicit or explicit learning, or a complex interaction between the two types of memory. It also allows for a theoretical approach to the small handful of exceptions in which memory phenomena that appear implicit with cognitively healthy participants appear to depend on the MTL memory system. The contextual cuing paradigm (Chun & Jiang, 1998) has been used to study implicit learning in attentional search such that improved search performance occurs with repeated stimuli, even when the participants are unaware of the repetition. However, this type of learning is disrupted with hippocampal damage (Chun & Phelps, 1999). The pattern is similar to observations from a paradigm of ‘priming of new associations’ (Graf & Schacter, 1985; Shimamura & Squire, 1989) that described a type of priming that was not preserved in amnesic patients. However, if the mechanism of implicit learning is pervasive throughout the brain, we can expect that it would apply even to shaping representations that were initially acquired from MTL-based (explicit) memory processes. This type of process would also support the statistical effects on explicit memory retrieval processes hypothesized by Anderson (Anderson & Milson, 1989) to account for how human memory adaptively responds to the observed demands of the environment.

Allowing for this interplay between types of memory allows for a very flexible theoretical account of a wide variety of observed human memory phenomena. However, it is based on a different approach than the original findings of robust dissociations between types of memory and might be criticized as exceedingly difficult to falsity. Even though the description is consistent with a very wide range of findings across memory systems research, it does not directly rule out alternate hypotheses. The primary alternate view of memory has historically been that human memory is largely based by a single system with the idea that this more parsimonious approach needs to be ruled out before accepting the more complex memory systems framework (Shanks & St. John, 1994; Nosofsky & Zaki, 1998). A single system or type of memory is largely inconsistent with neuroscientific observations of memory and the many systems demonstrating synaptic plasticity. However, a skeptic might suggest that although there is clearly neuroplasticity in the brain that operates outside awareness, the cognitively important aspects of human cognition depend exclusively on operations of explicit memory. Because human implicit learning phenomena have traditionally been studied with artificial paradigms aimed to dissociate implicit and explicit memory, it could be suggested that implicit learning is merely a vestigial reflex or a trick that can be elicited in the psychology or neuroscience laboratory.

To address this concern, it is necessary to examine how implicit learning affects cognitive behavior in designs that better capture the demands of memory imposed by activities in the world outside the laboratory. The utility of the memory systems framework needs to be shown as leading to a better understanding of complex learning processes and should be driven by a program of research in Applied Implicit Learning. This will entail eventually moving past reliance on the creative and unusual learning and memory paradigms (e.g., AGL, SRT) that were highly effective for isolating types of memory and developing the scientific framework. Among the immediate challenges for this new approach is that a theory of memory systems interactions is needed (e.g., Nomura & Reber, 2012) that the focus on dissociation has often overlooked (with notable exceptions, such as Poldrack et al. 2001).

In the remainder of this review, three research areas will be presented in which there is already evidence of influence of the core ideas behind implicit learning and memory systems and in which it appears further integration of the neurocognitive framework will be valuable. The first of these, “statistical learning” (Saffran, 2003) reflects a research area very much in the same tradition as the original AGL paradigm aimed at understanding the automatic extraction of statistical regularities to support language learning. Second, the process of “skill learning” and performance also naturally incorporates ideas about separate forms of learning from explicit instruction and repetitive practice. The memory systems framework captures these descriptions well and can guide theoretical accounts of the development of skilled expertise. Third, research on decision making (Tversky & Kahneman, 1975) developed in parallel a structurally similar multi-system approach to differentiate processes for rapid, intuitive decision making and slower, deliberate reasoning. This approach maps on fairly well to the memory systems framework and highlights interesting questions about the interaction of systems. This framework has been highly valuable in helping to understand certain classes of errors where implicit learning can lead to implicit bias affecting judgments. Across these three areas, consideration of the roles and interplay of multiple types of memory allows for better characterization and understanding of complex, real-world, human learning processes than can be supported by a simple, single system theory.

Statistical Learning and Language

The original AGL paradigm used to introduce the idea of implicit learning was developed in response to the introduction of computational linguistics. If human language can be represented in formal structures (finite state machines) that account for important aspects of syntax, how are these structures learned. While the AGL paradigm explicitly represented the underlying formal grammar structure, a different approach to the same idea was taken by Saffran, Aslin, & Newport (1996) with a paradigm described as "statistical learning." This approach used much simpler stimuli but was designed to be used to assess how pre-verbal infants could extract statistical structure from auditory speech-like input. The findings that emerged from this field of research were strongly influenced by considerations of the formal linguistics model of Chomsky (Saffran, 2003), just as the original A.S. Reber (1967) paper was. The paradigm developed by Saffran and colleagues focused on the statistics embedded in speech that could be used to determine word boundaries, rather than the syntactic structure implied by an AGL, and were designed to be amenable for developmental studies with pre-verbal infants.

In the statistical learning paradigm, infants (or other participants) listened to 2-3 minutes of artificial speech (synthesized) that contained an essentially undifferentiated stream of syllables. Statistical structure was covertly embedded by constraining the transitional probabilities between syllables in a manner similar to natural speech. In natural speed, phonemes within words are highly constrained but phonemes at the end of a word (on the boundary) can be followed by the initial phoneme of a much wider range of possibilities. After familiarization with artificial phoneme streams following this structure, infants exhibit differential preferential looking to stimuli that follow or violate this statistical structure. By careful control of the underlying frequency and conditional probabilities (Aslin et al., 1998) in a manner reminiscent of the controls discovered to be necessary with the SRT task (Reed & Johnson, 1994), it was established that these very young infants were essentially computing the transitional conditional probabilities among phonemes.

The statistical learning paradigm established a key idea behind the original AGL paradigm in that it showed that pre-verbal infants, in the process of natural language acquisition, exhibited a sophisticated learning ability that could support key aspects of language learning. In addition to the findings showing that word boundaries could be statistically extracted from continuous auditory input, additional findings extended this type of learning to more abstract relational rules (Marcus et al. 1999) and to some kinds of non-adjacent dependencies (Newport & Aslin, 2004). These paradigms do not attempt the complexity of formal linguistic structures necessary to acquire and produce well-formed, syntactic language. However, the statistical learning findings do show a core learning ability that emerges from experience and shapes processing of auditory input to support language processing. Of particular note, this implicit learning mechanism is available and relatively computationally complex even in young infants who are acquiring language.

Extensions of this line of research further suggested that statistical learning ability is not restricted to linguistic stimuli, with statistical learning being exhibited by infants in the visual domain as well (Fiser & Aslin, 2002; Kirkham et al. 2002). Using paradigms that parallel the auditory presentation of covertly embedded statistical information, infants and adults exhibit sensitivity to this structure in sequences of visual objects (Fiser & Aslin, 2002; Turk-Browne et al. 2005). These findings suggest that the ability to extract statistical structure are present across sensory modalities, generally supporting the idea of widespread neural plasticity supporting implicit learning to reshape processing throughout the brain (P.J. Reber, 2013).

Although the statistical learning paradigm was also extended to adults, attempts to assess the conscious accessibility of the statistical structure did not immediately follow. Since this research area emerged from developmental studies, the tools developed to assess awareness of learning were not applied to the adult learning paradigms. Even so, the commonalities between implicit and statistical learning were noted as likely emerging from the same underlying mechanism (Perruchet & Pacton, 2006). Batterink et al (2015) systematically evaluated contributions from both implicit and explicit memory to statistical learning to support the idea that even in adults, this form of statistical learning depends on mechanisms that support implicit learning.

While statistical learning is able to play an important role in language learning, it is clear that not all language processing depends on or can be learned entirely implicitly. Some crucial elements such as reference and work meaning seem to depend on the MTL memory system that is better suited to supporting memorization of the connection between a vocabulary word and its referent. This observation has led to the description of language processing as depending on both kinds of memory (Ullman, 2004; Paradis, 2004) contributing materially to different aspects of this complex process. Morgan-Short et al. (2010) applied this theory to questions of second language acquisition suggesting that a multiple systems model of language acquisition can provide valuable insight into how a second language is learned.

As seen across the three areas of ‘applied implicit learning’ considered here, connections of implicit learning and memory systems theory to non-laboratory applications generally require considering both types of memory and also potential interactions between memory systems. Considering learning a second language as an example, we would hypothesize that the new syntactic structures to be learned might be best acquired by high levels of exposure to speech to allow for statistical learning to proceed. Memorization of new vocabulary would be facilitated by strategies that facilitate explicit learning (e.g., deep semantic encoding). However, an unanswered question in this area is how these two types of memory interact during the learning process. Do statistical learning and word memorization support each other, proceed independently or even interfere with each other? To date, within language studies questions about system interactions have not been thoroughly explored. As in many areas within implicit learning, the drive to isolate this type of learning has led to the development of tasks aimed at separating memory types rather than examining interactions.

Skill Learning

A research area in which the potential importance of interactions among memory types has begun to be considered is the acquisition of expert skill. While skills are often initially learned with some explicit instruction, the importance of practice in acquiring expert levels of skilled performance has long been understood. What is learned during the process of repetition is not easily available to conscious awareness but accrues through experience. Early research in psychology aimed to characterize this process of skill learning and improvements in performance due to repeated practice (e.g., Fitts, 1964). The course of learning measured as performance improvements from practice has been extensively studied and is often described as following a power-law (Newell & Rosenbloom, 1981; or some similarly negatively-accelerated curve) that continues over remarkably extended periods of time, even up to millions of repetitions (Crossman, 1959). Within this field, there are active debates over the role of rote practice, structured deliberate practice (Ericsson et al. 1993) and other factors (such as talent) that predict expertise (Campitelli & Gobet, 2011). However, this process is fundamentally a memory phenomenon that must be supported by the learning and memory mechanisms of the brain.

There is a basic assumption embedded in any approach based on practice that the information acquired during practice could not have been acquired by explicit, verbal instruction, which would otherwise be much more efficient. The information learned during practice is generally not available to later verbal report, suggesting that implicit learning mechanisms are playing an important role. The nonverbal nature of this knowledge might alternately be ascribed to the type of representation, i.e., “motor learning” might not support verbally accessible representations. However, the memory systems framework incorporates this idea by including learning within specific neural systems such as motor execution (or perceptual learning) as varieties of implicit learning in that they do not depend on the MTL memory system and produce knowledge representations that cannot be described.

Many of the tasks examined in the general domain of skill learning are not simple motor or perceptual learning tasks. Cognitively complex skill such as playing chess are initially learned through explicit instruction but expertise only emerges after extensive practice (Ericsson et al. 1993). Within music cognition, the different roles of explicit memorization and learning from practice are well-understood. Chaffin, Logan & Begosh (2011) describe in detail two parallel processes of preparing for expert music performance, one based on building associative chains while repeatedly practicing and a separate process of explicitly memorizing the written score (as a backup in case of error). The memory systems framework provides a useful way of characterizing these learning processes. Memorization of the music piece depends on explicit memory and the MTL memory system. Practicing the piece allows for the pervasive neuroplasticity mechanisms supporting implicit learning to hone neural processing to make execution of performance smooth, precise and accurate.

However, the fact that this framework is consistent with descriptions of skill learning does not establish that the account is accurate. One of the challenges in studies of complex skill learning is the necessity of both explicit and implicit instruction during the learning process. Because these always co-occur, alternate hypotheses about skilled knowledge representations need to be considered. One possibility is that skill learning produces a functionally integrated representation across memory types such that a independent systems model cannot aid our understanding of this process. Another possibility is that repeated practice changes the character of an initially explicit memory representation such that retrieval becomes so rapid, effortless and automatic that there is no role (or need) for implicit learning processes.

Laboratory research aimed to capture the skill learning process in order to address these alternatives has largely focused on tasks of perceptual-motor skill learning such as the Serial Reaction Time (SRT) task.

The SRT task (Nissen & Bullemer, 1987) is a highly studied task that appears to be largely supported by implicit learning. Participants perform a serial 4-alternate forced choice response task in which the sequence of cues covertly follows an embedded sequence. Faster reaction times when the cues follow a practiced sequence compared with conditions where the cues follow an unfamiliar sequence are evidence that the practiced sequence has been learned. Establishing that this learning is solely implicit would provide robust evidence for the memory systems framework in skill learning. This kind of direct implicit learning without initial explicit memorization makes it clear that skilled performance does not necessarily depend on either an integrated implicit/explicit knowledge representation or automation of initially explicit knowledge.

However, while the first demonstration of learning with the SRT task suggested both knowledge outside of awareness and intact learning by memory-impaired patients (indicating lack of dependence on the MTL memory system), debates about the character of knowledge acquired during the SRT task have persisted. Thorough investigations of the conscious access of sequence knowledge (Perruchet & Amorim, 1992; Willingham, Greely & Bardone, 1993) suggested that sensitive tests of sequence recognition almost always indicate some explicit knowledge in healthy participants. Having some conscious memory of the repeating sequence might reflect the concomitant operation of the MTL memory system (in cognitively healthy undergraduate participants) or might reflect evidence for the alternate hypothesis that skill learning depends on integrated representations. Studies of amnesic patients (Reber & Squire, 1994; 1998) showed that reliable learning could be observed in the absence of explicit memory, but concerns remained about the ability to prove intact learning in patients (which necessarily depends on a finding of a null difference between patients and controls). Destrebecqz & Cleeremans (2001) reported a strong dissociation between implicit and explicit sequence knowledge for a specific variant on the SRT design (zero delay in the interval between response and next cue). Overall, while the evidence supported the idea that learning was implicit, the difficulty of regularly finding evidence for process-pure implicit learning with the SRT task meant questions about representation persisted.

A new variation of the sequence learning paradigm was described by Sanchez, Gobel & Reber (2010) as a Serial Interception Sequence Learning (SISL) task. This paradigm changed the basic task performed by the participant. Rather than a simple speeded response to the onset of a cue (in one of four locations), cues appear, then move vertically down the screen toward a target area, and the participant has to time an ‘interception’ response of pressing the correct response key precisely as the cue reaches the target area. Just like in the SRT task, the cues follow a repeating covertly embedded sequence but the additional cognitive demands of the response task appears to reduce the degree to which explicit knowledge is acquired. Sequence knowledge is measured by accuracy (a properly timed response is correct, mis-timed or incorrect keypress are incorrect) during the repeating sequence compared with accuracy during an unfamiliar sequence. Sanchez, Gobel & Reber (2010) showed that learning on the SISL task is solely implicit for a substantial subset of cognitively healthy participants in a typical experiment. Showing robust learning with zero apparent explicit knowledge in approximately a third of participants provided strong evidence that the SISL task could be learned in the absence of explicit knowledge, arguing against integrated representations. In a follow-up study, Sanchez & Reber (2013) found that giving participants full explicit knowledge of the embedded sequence did not affect performance on the core task, providing strong evidence that implicit learning drives performance and that any explicit knowledge obtained by noticing the repeating cues does not materially contribute to accurate responding in the SISL task (in contrast to the SRT task where explicit knowledge can lead to negative reaction times where participants respond before cue onset). Neuroimaging during the SISL task found that learning was associated with greater efficiency in neural processing for the practiced, repeated sequence as would be predicted by adaptive neuroplasticity (Gobel, Parrish & Reber, 2011). Neural changes were largely in cortical regions, although increased activity suggested a role for the ventral striatum. A neuropsychological study of memory-impaired (amnestic MCI) patients and patients with Parkinson's disease (PD) found impaired learning in the PD patients but intact learning in the MCI patients, reinforcing the importance of the basal ganglia rather than the MTL for sequence learning (Gobel et al. 2013).

Across each of these studies, knowledge of the embedded repeating sequence was found to be extracted implicitly from practice and used to enhance task performance (when the cues follow that sequence). Because this happens without initial explicit cue knowledge and independently of the MTL, the memory systems framework provides the best account of the learning process as based on separate neural systems for implicit and explicit sequence knowledge. Theoretical accounts based on skilled performance emerging from integrated representations or explicit knowledge automated through practice can not account for these findings. Beyond a consistent description, the memory systems framework also guided a series of additional studies seeking to better characterize the implicit learning component of skill learning with a goal of understanding skill training and education outside the laboratory.

A key challenge in skill learning is the degree to which learning is inflexible, leading to poor performance in novel but related transfer tasks (Adams, 1987) which may be due to the role of relatively inflexible implicit learning (Cleeremans, Destrebecqz & Boyer, 1998). Using the SISL task, sequence learning was found to be highly specific and inflexible such that small changes in inter-cue timing (Gobel, Sanchez & Reber, 2011) or perceptual characteristics (Sanchez, Yarnik & Reber, 2015) led to nearly complete elimination of the accuracy advantage for practiced sequences. This inflexibility may have the practical consequence of making implicit knowledge occasionally inaccessible, perhaps explaining the need for expert musicians to separately memorize the written score prior to performance (so that explicit memory could be used to rescue performance if implicit knowledge was unexpectedly unavailable).

In contrast to this constraining aspect of implicit learning, Sanchez & Reber (2012) found robust implicit learning for surprisingly long repeating sequences in the SISL task (up to 90 items) and that learning appeared to be log-linear with practice regardless of sequence length, meaning long sequences were learned as rapidly as short ones (except that they took longer to complete). The ability to learn very long sequences indicates that implicit learning can support the kind of memory described by musicians during the 'learning' phase of repetitive practice in which performance is honed for a piece that will contain large numbers of sequential actions. An extension of this kind of long sequence learning into an applied context was described by

Bojinov et al. (2012) in which participants implicitly learned a long sequence that was then used as part of security authentication as an implicit password. A password learned this way has useful security implications as it cannot be shared (or coerced) and reflects the use of implicit learning and memory systems theory in an attempt to guide non-laboratory applications.

This theoretical framework has also been applied to research examining the effect of stress (pressure) on the performance of trained skills (DeCaro et al., 2011). Beilock and colleagues described a theory of 'choking' under pressure in which explicit monitoring of a skill learned implicitly led to decrements in expert performance (Beilock & Carr, 2001). Flegal and Anderson (2008) reported a similar phenomenon in skilled performance in experts as verbal overshadowing reflecting competition between memory systems. These types of findings are difficult to understand without utilizing the memory systems framework that incorporates different types of memory with different operating characteristics and separate neural mechanisms. Being able to study each system independently has also recently revealed that implicit learning and/or performance can be influenced by factors such as mental fatigue (ego depletion; Thompson et al., 2014), motivation (Chon et al., in press) or even hypnosis (Nemeth et al., 2013). As skill learning is foundational to education (cognitive skills), training and the development of expertise, implicit learning and the memory systems framework will provide critical guidance to basic science research applied to improving learning in skill learning contexts.

Decision Making

A research area in which the roles and interactions among multiple systems has a fairly substantial history is the process of decision making. In his remarks upon accepting the Nobel prize in economics, Kahneman (2003) described the framework developed by his work with Amos Tversky as emerging from two cognitive systems. Intuitive reasoning depends on System 1, a processing system characterized as: rapid, automatic, effortless, associative, slow-learning and emotional. In contrast, System 2 reasoning is deliberate, slow, controlled, effortful, rule-governed and flexible. These system definitions mirror the memory systems model of implicit and explicit learning with many of the same descriptive terms applied to features of each type of processing. However, this line of research was largely developed independently and was primarily applied to research on behavioral economics and decision-making without direct connection to the role of memory.

Within this line of research, a notable difference is the focus on the speed of processing rather than the availability of knowledge to conscious awareness or underlying neural systems. Descriptions of decision-making within this framework typically describe a fast System 1 response than can be then reviewed and potentially overridden by a slower System 2 response. This type of interaction across systems is different than those considered within skilled expertise (or language processing) but might be hypothesized to play a role in those domains as well.

This approach lends itself to research examining the phenomenon of intuition (e.g., Klein 2004) defined as a System 1 process that rapidly identifies an action to take that is often subjectively described as based on a 'gut hunch' or instinct. This type of intuitive decision making (IDM) has been studied for its potential to support rapid, expert, accurate decisions that are of great value in complex and/or stressful environments. That approach is somewhat different than the early focus of Tversky & Kahneman (1975) that focused on erroneous (non-rational) decisions driven by biases that could emerge from System 1 processes. Kahneman & Klein (2009) contrasted and compared a System 1 and 2 account of this process with research obtained through naturalistic decision making research based on analysis of experts making complex, high leverage decisions in the field. They determined that their approaches were largely in sync and suggested that prior experience in the decision-making context was an effective predictor of the accuracy of intuition. This idea was explored and directly supported empirically by Dane, Rockmann & Pratt (2012) by comparing the accuracy of intuition across different levels of domain expertise. High domain expertise led to much more accurate intuitive judgments, as would be expected if intuition was supported by implicit extraction of the statistics of the environment during the acquisition of domain knowledge.

This conclusion fits well with the memory systems model derived from laboratory studies of implicit and explicit memory. Implicit knowledge of a specific domain is accumulated as part of the development of expertise based on refining and honing processing (as in skill learning) in addition to statistical learning of environmental features (as in language learning). The resulting implicit knowledge structures reside outside awareness due to their dependence on plasticity separate from the MTL memory system (which will provide episodic memory of specific examples and salient events from experience). We can also connect this idea to laboratory studies of implicit learning where participants are asked to make a response, e.g, about grammaticality of an unfamiliar letter string, but report they feel as though they are just guessing even when their performance is significantly above chance (Reber, Beeman, & Paller, 2013).

However, an unanswered question in memory research is the route by which this information proceeds through the brain in order to actually guide action selection. Using laboratory studies of visual category learning in which participants are required to learn categories through a process of trial and error as a model, Nomura & Reber (2012) described a multi-system model of category learning and performance, PINNACLE, that incorporated two separate processing streams for information extracted implicitly during learning and memorized knowledge of the category stimuli. This model has the structure of a “mixture of experts” model at the decision-making level with the response decision (the participant’s response about which category the stimulus was thought to belong to) being influenced by either implicit knowledge via intuition or explicit knowledge by deliberate application of conscious task knowledge.

The PINNACLE model was developed in reference to a well-established laboratory paradigm for studying category learning (Ashby et al., 1998; Ashby & Maddox 2005) in which known manipulations to the underlying category structure could lead participants to rely on an explicit, rule-based (RB) strategy or an implicit strategy based on integration information across dimensions (II). In this task, participants are shown artificial stimuli that vary in two dimensions, such as sine-wave gratings that vary in spatial frequency (line thickness) and tilt. They attempt to learn how the stimuli are organized into two underlying categories by trial-and-error with feedback after each response. When the structure is determined by a simple rule, participants generally discover the rule, use it to make their category membership decisions and verbally report the rule after learning. Complex, multi-dimensional rules often drive behavior differently with participants exhibiting gradually increasing accuracy at the task but without being able to report the basis of their judgments.

Using neuroimaging, Nomura et al. (2007) showed that neural activity associated with rule-based learning occurred within the MTL memory system. In contrast, II learning was associated with increased activity in posterior regions of the caudate, brain areas often associated with implicit learning plasticity (Seger & Miller, 2010). Using the PINNACLE model to probe the neuroimaging data in more detail, regions in the prefrontal cortex were identified that were associated with the cognitive process of selecting which strategy to apply on a single decision. The resulting model lines up well structurally with the Kahneman (2003) framework with separate neural systems contributing to rapid, intuitive decisions and slower, deliberate and explicit decisions. Interactions between the two modes of decision-making would occur within the dorsolateral prefrontal cortex which would reflect a meta-level decision such as knowing when to 'trust one's instinct' to guide behavior.

The PINNACLE model provides a method for translating the laboratory studies of multiple brain systems into non-laboratory applications. P. Squire et al. (2014) described how research in this direction could be used to study the processes of intuitive decision making and generate hypotheses about how decision making expertise could be trained more rapidly. A similar approach was used by Dane & Pratt (2007) in their analysis of how treating intuitive and non-intuitive decision making in managerial contexts could be informed by the multiple memory systems model. In a number of these cases, attention is also paid to erroneous decision making that can emerge from reliance on intuition (Kahneman & Klein, 2009). A balanced model of the value of intuitive decision making emerges naturally from an implicit learning approach. Implicit learning can only reflect experience and the statistical structure of the environment in which it was acquired. Thus intuitions may be quite inaccurate in novel contexts where the environmental statistics are different than prior experience. In addition, implicit learning through practice can just as easily reinforce consistently erroneous decisions, i.e., bad habits can be learned as easily as expert performance.

A research area focused directly on the potential negative consequences of our automatic implicit learning is studies of stereotype prejudice that are based on 'implicit attitudes' (Greenwald et al., 2002). The core idea in these studies is that experience in an environment shaped by the existence of stereotypes will tend to shape individual's cognitive processes to reflect these prejudices. The result of this process is that stereotypical information is represented outside awareness, leading individuals to not even realize that their responses and decisions are being influenced by this implicitly acquired bias. This implies a very different model of prejudice in which stereotype-driven decisions and responses are not knowingly based on dislike of an outgroup but are based on something closer to a negative form of intuition. This model fits very well with the initial descriptions of decision-making biases originally characterized by Tversky & Kahneman(1975) in accounts of apparently non-rational decision-making behavior. Thus, statistically-induced biases in cognition that are acquired via implicit learning can enhance decision-making performance, but there is also a potential negative side where environmental bias will become reinforced through the same mechanism.

Conclusions

While neuroscientific studies of memory leave little doubt that there are multiple mechanisms of synaptic change in different systems across the brain, this observation does not indicate what roles different types of memory in complex human behavior. Phenomena characterized as implicit learning in laboratory studies have shown how prior experience can influence current behavior without awareness of the information previously acquired. However, the cognitive consequences of this type of memory are most clearly seen when examining applications of memory systems theory outside the laboratory. Research examining human decision making, skill acquisition and language learning have all converged on theoretical frameworks that are highly consistent with the basic multiple memory systems model derived from cognitive neuroscience research. Whether these separate processes are called System 1 and 2, instruction and practice, or syntax and semantics, independent roles are seen for learning from both the statistics of experience and also conscious memorization of prior episodes. Thus applied learning and memory research is well captured by the memory systems model of P.J. Reber (2013) which posits widespread non-MTL neuroplasticity as the basis for implicit learning as a separate type of memory than that supported by the MTL.

Applying the memory systems framework to questions of learning in non-laboratory contexts highlights some gaps in many current programs of memory research. In language use, skill learning and decision making, identifying important roles for both types of memory immediately indicates a need for hypotheses about how these systems interact. Since the main focus in memory systems research to date has been focused on isolating memory types, most laboratory paradigms have not confronted questions about the interplay among systems. In contrast, in decision making research the potential for slower, deliberate processing to override a fast, intuitive response is a core hypothesis. In addition, basic questions about how we learn to trust and use our intuition are not addressed within the memory systems model. Trusting one's gut instinct appears to imply a meta-cognitive process for evaluating the quality of our implicitly help knowledge, which is a counter-intuitive construct since the implicit knowledge is theoretically outside of awareness. Within skilled performance, the example of expert musicians both learning and memorizing a piece to be performed indicates a different kind of interaction. Here, the implicit, practice-based knowledge is not seen as inaccurate but occasionally and unpredictably unavailable, requiring redundant memory representations to support performance. Skilled performance can also reveal negative interactions between memory systems in a model of 'choking' where explicit processing interferes with expert implicit processing (Beilock & Carr, 2001). Within the domain of language, the role of extracted statistics from prior experience seems as if it must function in a much more closely synergistic manner with conscious aspects of linguistic processes in order to communicate, a fundamentally conscious process.

Laboratory studies of phenomena related to implicit learning over the past 50 years have established tools and paradigms for characterizing and studying this phenomena. Applied, non-laboratory research instead lept ahead, assuming a basic implicit/explicit multi-system model and found it provided explanatory power in a range of domains. A common framework unifies these approaches build on two memory mechanisms in the brain. Widespread neuroplasticity leads to adaptive rewiring of neural circuitry to improve performance and increase neural efficiency. This mechanism leads to knowledge embedded in performance structures that is implicit and unavailable to conscious report. The MTL memory system supports acquisition and consolidation of episodic memory, prior experiences of facts and events, that are retrieved consciously and used flexibly and creatively. Both research approaches then point to the need for theoretical development at the interaction between systems to understand how information represented in such different ways can support complex human cognition.

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