Human Memory Systems: A Framework for Understanding the Neurocognitive Foundations of Intuition

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Abstract. A neurocomputational framework is described for characterizing how intuitive and deliberate processing are accomplished in the human brain. The framework is derived from memory systems theory and supported by research findings on contrasts between implicit versus explicit (nonconscious versus conscious) memory. Implicit intuition and deliberate deduction depend on separate types of memory supported by distinct brain networks. For optimal decision making, training should be designed to accommodate the operating characteristics of both types of memory. Furthermore, reliance on explicit memory can inhibit the use of implicit intuition, so training must facilitate effective interactions between the two types of mechanism. To aid investigations of these effects, we introduce a Mixture-of-Experts model that characterizes the interaction between memory systems — the PINNACLE model (Parallel Interacting Neural Networks Competing in Learning). This model captures the separate neural networks that reflect implicit and explicit processing, as well as their interaction, and it can thus guide the development of training approaches to maximize the benefits of concurrent use of both intuition and deliberation in decision making.

Keywords: Intuition, decision making, implicit, explicit, memory systems, cognitive neuroscience, cognitive modeling.

1 Introduction

> *A fireman in Cleveland cleared his team from a fire scene because he "sensed" that something was odd about the situation. Indeed, the floor was about to collapse because of a raging fire below. The lieutenant fireman who saved his men was not aware of the danger in the usual sense, but rather he was observant enough and skilled enough to know that something was not right. He acted on that indication before consciously realizing what wasn't right or what danger was present. At first he thought it was ESP. Only much later did he begin to understand the clues he had sensed.* [1-2].

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This story exemplifies the successful use of intuition in a high-pressure problem-solving environment. The profound action that saved these firefighters can be credited to implicit processing of the environmental cues, leading to escape from an imminent catastrophe. Decades of research on implicit learning have shown that our brains possess an array of mechanisms for automatically extracting information from the environment without our awareness [3]. The results of this implicit learning often appear as an intuition or a "sixth sense" about the current situation. Intuition typically emerges with no awareness of the mental events leading to it, which fits with our conjecture that implicit memory is critical in producing trustworthy intuition. Our framework builds on a substantial body of research on implicit memory in order to elucidate how this distinct yet powerful type of processing can support reliable decision-making.

Our prior research has identified neural correlates of implicit memory that we can measure to reveal implicit influences in complex tasks [4-5], and the emergence of implicit information when people solve with sudden insight [6]. We have also described a computational model to characterize the interaction of implicit and explicit processing [7]. That model, PINNACLE (Parallel Interacting Neural Networks for Competitive Learning) will be used as a basis for characterizing the neurocognitive processes involved in intuitive decision-making influenced by implicit processes. Two key features of this model are: (1) it incorporates separate processing streams for explicit deliberative processing versus implicit intuitive processing, and (2) it includes a neurocognitive architecture to test hypotheses about how these types of processing compete with each other, or conjointly produce decisions. This model makes distinct predictions about the neural basis of interactions among types of memory that can be explored and tested with functional neuroimaging approaches.

Laboratory studies of implicit learning have typically found the greatest influence of implicit knowledge when people feel they are just guessing. When implicit and explicit processing are pitted against each other in experiments, the systems often appear to compete such that only one system can influence behavior. For instance, when explicit problem solving is actively engaged, a contribution from implicit intuition is less likely, suggesting that deliberate processing can actively block the use of intuitive knowledge. Although such an arrangement seems suboptimal from a human information-processing perspective, it may reflect a characteristic of the human neural architecture that needs to be understood in order to enable the best use of implicit intuition. Findings of competition among memory and decision-making systems raise important questions about how to optimize teaching and training programs to maximize the ability of a trainee to incorporate both sources of information effectively.

The PINNACLE framework is constructed as a Mixture-of-Experts model in which independent processing streams feed information forward to a high-level cognitive process, which resolves competition and selects a response. A special feature of this model is that one stream operates outside awareness so that subjective introspection yields limited information about how this information affects behavior. Of note, the high-level decision process can function to inhibit the use of either type of information, consistent with empirical observations of competition between memory types. We hypothesize that this meta-cognitive process can be separately trained to foster better use of both types of information and reduce inter-system competition between types of memory.

This framework enables us to test critical hypotheses about people who act based on intuition, as did the fireman in Cleveland. In his case, his prior learning about dangerous environments apparently enabled a novel pattern of cues to prime the suspicion that the floor was about the collapse. Just before this happened, what explicit processing was also engaged? How did implicit information emerge at the critical moment, and avoid suppression, to allow him to take the life-saving action? Why do others fail to be heroes in such circumstances?

If we looked into the brain of the fireman just before he saved his team, we would expect to see neural activity associated with implicit environmental pattern detection. Yet, the fireman thought that at that moment he was supernaturally able to predict the future. Given the competitive nature of implicit and explicit processing, we predict a dearth of neural activity in regions responsible for the deliberate processing of environmental cues to danger. Rather, the implicit processing of those cues likely predominated. In some domains, however, intuitive processing appears to coexist with explicit processing with less detrimental competition. During problem solving, for example, participants can be actively and explicitly searching for solutions when an insight suddenly emerges [6]. What factors facilitate the emergence of intuitive strokes of genius?

2 Mixture of Experts Model: PINNACLE

A key challenge for understanding how we use intuition in problem solving is that intuition depends materially on the result of implicit learning mechanisms that are represented in separate neural systems from deliberative problem solving. The proposed research addresses this challenge using a computational modeling approach that incorporates multiple information processing streams that are combined at the final decision process. The general PINNACLE framework is a Mixture-of-Experts (MoE) cognitive architecture, shown in Figure 1.

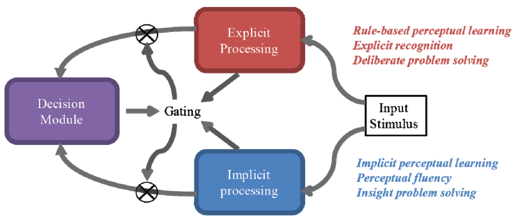

Fig. 1. General Mixture-of-Experts Cognitive Architecture of PINNACLE. Information flows from right to left from input through two parallel processing streams, explicit (upper) and implicit (lower). Three examples of explicit and implicit processes assessed in laboratory empirical studies are shown. The results from these independent processes are evaluated in a final Decision Module. Gating processes reflect competition and potential inhibition between types of processing.

Under this modeling approach, environmental information (stimulus input) is available to implicit and explicit processing streams that each operate independently in different areas of the brain. Information feeds forward to a decision module where a single behavioral response is selected as an action or decision. In addition, the model allows for a gating process to inhibit or enhance processing in one stream or the other. This architecture captures situations where strategic factors cause decision making to be locked into one mode or another—such as when a person is exclusively focused on explicit processing and no influence of implicit processing or intuition is evident. In this case, implicit processing is dormant due to inhibitory gating from the explicit process. Yet, this situation can theoretically be remedied via training to block the gating process so that implicit information can be used.

Most theories of problem solving and decision making have focused largely on processing represented in the explicit processing stream that reflects conscious, deliberative analysis of input. The effects of implicit processing appear occasionally as a sudden intuition that, when accurate, reflects the operation of nonconscious processing or memory. Decades of memory systems research have established the existence of these multiple types of processing in the human brain and provided hypotheses about the neurocognitive basis of each type of memory. However, very little research has examined the important practical questions of how information across regions may be effectively combined to guide decision making.

Three examples of how the PINNACLE framework is applied to laboratory studies of implicit and explicit processing are described here. Each example uses a different type of complex decision that can be made based on either implicit or explicit processing. Capturing these complex and interacting processes in our framework shows how the neurocognitive foundation of implicit intuition can be modeled.

2.1 Applying PINNACLE to Perceptual Learning

The PINNACLE model was first developed and applied to studies of perceptual skill learning in a visual category-learning paradigm. The visual category-learning paradigm presents participants with sine-wave gratings organized into two unknown categories that are learned during an experimental session via trial-and-error feedback. Two conditions are used to separately examine deliberate rule-based processing and implicit (termed "information-integration") category learning. Conditions conducive to RB learning are created by using a category structure that can be easily described as a rule about the stimuli. The rule is discovered by participants readily, leading to subsequent explicit rule-based category judgments. When the categorization rule requires using information across stimulus dimensions and does not lend itself to an easily verbalized rule, learning depends on implicit memory and accurate performance is not accompanied by awareness of the category structure.

To simulate both types of behavior, PINNACLE was developed with two core component processes: a rule-based learning system and an information-integration learning system. External stimuli feed information into these two parallel processing streams, which propagate information to a Decision Module, where the categorization decision response is made [7]. Each of the processing streams (the internal "experts") is simulated using a Decision Bound Theory (DBT) mathematical model that produces a category membership estimate learned from experience, but that is constrained to only consider either rule-based or information-integration hypotheses. The DBT formalism provides an estimate of the probable category membership of a stimulus as a function of its distance in perceptual space from the category boundary, and weighted by a perceptual shaping parameter that decreases the strength of the position near the boundary conditions, where uncertainty is higher [8-9]. At the beginning of a simulated experiment, the structure of the category to be learned is not known, and both internal models attempt to learn the category via feedback. On each trial, both systems update internal representations of the category in order to improve future predictions by an error-minimizing adjustment to the current state.

The modeling process operates in two steps. In the first step, a multi-system computational model is fit to overall group behavior to establish a basic working model. In Nomura and Reber [7], we showed that groups of model simulations fit average human behavior for both kinds of category learning without needing any advance knowledge on the type of category being learned. For the second step, each individual's performance within a learning session is fit using maximum likelihood estimation to provide a model of their cognitive state during each response trial, for both the internal implicit and explicit learning processes. Free parameter values are identified that maximize the likelihood of each response in the observed sequence of behavior using a downhill simplex optimization method shown to be effective for this process [7]. We can then identify key behavioral choice moments from data collected during functional neuroimaging based on predictions of the mental state of the participant and the estimated roles of the implicit and explicit processing streams. In Figure 2, brain activity indicating the neural correlates of the separate implicit and explicit processing streams and with the process of resolving these competing sources of information is shown derived from this method.

The application of the PINNACLE framework to implicit and explicit processes in visual category learning provides a demonstration of how this modeling approach can be used to establish the neurocognitive foundations of both types of memory in complex decision making. By providing the ability to assess neural activity across both types of processing, we can observe when and how implicit intuition can be effectively brought to bear on explicit processing. In addition, when competitive interactions among types of memory reduce the use of implicit intuition, the neural basis of this effect will provide a measure of effectiveness of potential interventions to reduce competition and improve training.

2.2 Applying PINNACLE to Recognition Memory

Another example of a decision process that is potentially affected by both implicit and explicit processing is that required to make a judgment about prior occurrence (e.g., have you see this stimulus previously?). In a recognition memory test, processes of implicit and explicit memory can both contribute to accurate performance [9]. Although a recognition judgment is conventionally taken to be a straightforward test of explicit memory, our recent work has shown that a correct response can also be produced based on a contribution of visual perceptual fluency. Explicit recognition judgments use a recognition cue (such as a word that may have been presented in a prior study list) to elicit explicit retrieval for the same item from the past (which may in some cases also include recall of relevant contextual features of a prior learning episode). However, the recognition cue can also be processed more efficiently because of the prior episode. This repetition-based efficiency is often ascribed to a boost in the fluency of perceptual processing of the cue. Responses that are seemingly guesses can actually be based on fluency signals, when an old item is selected in a recognition test without any awareness of memory for the relevant past experience.

In a series of studies [5,10-12] we have shown that we can boost the implicit memory contribution to recognition with the following set of procedures. Memory for single kaleidoscope images (each created with a unique algorithm using three colors) was tested using a two-alternative forced-choice test. The correct choice was a stimulus seen 1-2 minutes earlier; the foil choice was a very similar stimulus creating by altering the algorithm slightly, such that the decision was very difficult. Sets of stimuli were learned under divided-attention conditions, in which elaborative encoding was limited due to the concurrent demands of an auditory working-memory task. During the test, participants were encouraged to guess, and choices were made quickly using a 2-second response-signal procedure. Results were unlike standard findings for explicit memory, in that recognition accuracy was higher after divided- than full-attention encoding, and higher for guess responses compared to confident or familiarity responses. In addition, electrophysiological evidence implicated implicit perceptual fluency in accurate recognition guesses in these conditions that emphasized the use of implicit memory as opposed to explicit retrieval.

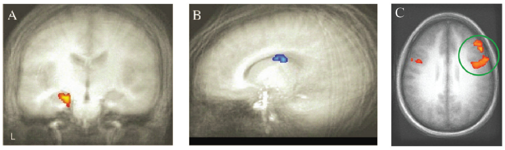

Fig. 2. Neural correlates of key brain systems involved in categorization decisions. (A) Medial temporal lobe activity associated with explicit memory for prior examples. (B) Posterior caudate activity rrelates of key brain syste associated with implicit learning. (C) Dorsolateral prefronal cortex activity associated with resolving competition between implicit and explicit processing.

On any trial in this recognition test, a correct response can be mediated by visual fluency or by explicit retrieval. We observe brain activity associated with either type of memory in EEG signals, computed by averaging trials for different judgments together. One indication of the type of response comes from metamemory judgments; participants can either indicate confidence in their response (i.e., conscious, explicit retrieval) or they can indicate a response made on no known basis whatsoever (guess). These highly accurate guess responses are what we term “implicit recognition” [9]. Judgments may also be made on the basis of implicit fluency signals in a variety of other decision-making circumstances.

By creating conditions wherein implicit recognition occurs on a large proportion of trials, the PINNACLE framework provides a method for examining the neurocognitive foundations of both types of processing and also potential interactions between the two types of memory. A key question is whether and how explicit retrieval blocks or interferes with the use of implicit knowledge. A focus on explicit memory retrieval appears to limit the extent to which implicit information is available for making a memory decision; both the number of guesses and the accuracy of those guesses is reduced by changing the instructions to emphasize confident responding [11] or by interfering with brain activity in prefrontal cortex [Lee, Blumenfeld, & D'Esposito, unpublished manuscript]. Paradigms that overcome this inhibitory (gating) effect will serve as a model for training the ability to simultaneously use both implicit and explicit memory in complex decision-making.

2.3 Applying PINNACLE to Insight Problem Solving

The third example domain for examining interactions between implicit and explicit processing is the laboratory study if insight-driven problem solving. In general problem solving, people can achieve solution using analytic processing, sudden creative insight, or both [6,13]. Analytic solving relies heavily on step-by-step processing and deliberate manipulation of consciously accessible information with explicit awareness of the contents and strategies engaged. In contrast, insight solving occurs when a person suddenly becomes aware of a solution, without conscious access to the solving process. Thus, compared to analytic solving, insight is more influenced by implicit memory and implicit processes generally.

Recently we've examined and manipulated factors that modulate the degree to which analytic and insight processes contribute to solving problems. In order to elicit robust numbers of both analytic and insight solutions, we've most often presented people with a large number of Compound Remote Associate (CRA) problems, in which they view three problem words (e.g., pine, crab, sauce), and must produce a solution word that can form familiar compounds or two-word phrases with each of the problem words (apple: pineapple, crabapple, apple sauce) [14]. On average, people can solve about half of these problems, and about half of the solutions occur with each type of solving. In numerous studies, participants indicate how they solved each problem, by analysis or insight. Different solution types are associated with changes in behavior, neural activity, blinks, and eye movements, all indicating that the participants engaged in different processes prior to solution. Indeed, insight and analytic solving are associated with different forms of attention prior to engaging each problem [15], and even different baseline brain activity [16].

Moreover, mood differentially affects insight and analytic solving, with positive mood facilitating insight, most likely via changes in anterior cingulate cortex that modulate cognitive control [17]; and separate visual tasks that encourage highly focused external attention facilitate analytic solving, whereas visual tasks that encourage internal attention facilitate insight solving [18]. Using the PINNACLE framework, we can characterize these effects as emphasizing processing within either the explicit, deliberative processing stream or the implicit, intuitive processing that leads to sudden insight. Emphasis on one type of problem solving approach may be reflected as directly increasing neural activity within one of the processing streams or may be reflected in high-level decision making processes that indicate a strategic decision to rely on step-wise problem solving or to anticipate a sudden flash of insight. By examining the neurocognitive foundations of these interacting processes, the problem solving paradigm provides a useful model of the roles of implicit and explicit memory in a cognitively complex domain.

3 Designing Interventions to Improve Use of Intuition

The key questions for improving the use of intuition are focused on the gating and decision-making mechanisms that are engaged during integration of information between the implicit and explicit processing streams. A variety of approaches aimed at increasing reliance on implicit intuition are derived from our prior research on implicit learning. To evaluate these approaches, we can quantify the improvement in performance using these paradigms. In addition, the PINNACLE modeling approach makes testable predictions about how the underlying neural activity patterns are changed by successful training interventions.

For instance, to target improvements in the operation of gating and reducing interfering competition, we could attempt to improve intuitive decisions using metacognitive strategies that avoid overshadowing of implicit information by explicit processing. That is, we can reduce dependence on highly focused external attention. To boost the impact of implicit processing, we can train participants to induce inward-looking attention to quiet internal activations and associations [18]. To do so, we can combine methods for inducing inward attention (e.g., voluntary eye-blinks and overt eye fixations away from problem stimuli) with feedback based on both successful implementation of the attention strategy and successful intuitive decisions.

Another approach is to use trial-by-trial feedback in order to give participants a greater ability to internally monitor their experience of implicit visual fluency signals in recognition judgments, using reinforcement-learning mechanisms. This approach is based on the idea that trainees can gradually learn to use subtle visual fluency cues more often, such that implicit intuition plays a greater role in complex decision making or problem solving. The feasibility of this method to train participants to use fluency this way is supported by recent findings from exposing subjects to a situation in which previously unstudied items were less visually fluent than studied items—and reinforcing this connection with trial-by-trial feedback [19-20]. Whereas familiarity is typically attributed to old items because they are, on average, more fluently processed than new items, this manipulation led to a temporary reversal such that subjects acquired a tendency to attribute familiarity to items with less fluency. By analogy, trainees should be able to learn the contingencies between the beneficial use of visual fluency and positive feedback for correct decisions—and these habits will generalize to other circumstances wherein implicit processing can be beneficial.

A third approach to improving the use of implicit intuition is based on the hypothesis that people can be trained to more strongly weight the implicit processing stream during decision making. Such training would encourage the use of implicit knowledge. This hypothesis suggests that the use of implicit intuitive knowledge could be enhanced in scenario-based training based on rapid decision making with ambiguous cues by providing pre-training with tasks that rely on implicit learning. Experience with successful implicit learning would then be used as a training enhancement to increase the ability to integrate knowledge across information processing systems, producing increased decision-making ability.

These three ideas reflect examples of how it is possible to use information about the neurocognitive foundations of implicit intuition in decision making in order to learn how to better use intuition. As we better understand the neural processes associated with memory systems in complex decision making, it is likely that a wide range of additional ideas for training interventions can be developed.

4 Summary and Conclusions

Our computational framework, PINNACLE, provides a neurocognitive foundation for studies examining the interacting roles of intuition and planned, deliberate processing in complex decision-making environments. By connecting implicit and explicit processing directly to neural circuitry, we can develop strategies for studying these processes individually and also tackle the challenge of how these two types of memory interact. Training effects can therefore be attributed to behavioral change reflecting one type of memory or the other. Experts with strong intuitions based on implicit learning from extensive experience rely on a different type of neural processing than do individuals who have learned an explicit rule. In addition to simulation-based training to provide an analog to situational experience, enhancing the ability to apply this intuition alongside explicit rules will also be necessary to bring trained intuition to bear on complex real-world problems.

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