# Implicit Learning, Tacit Knowledge, Expertise Development, and Naturalistic Decision Making

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**Abstract:** Implicit learning involves the largely unconscious learning of dynamic statistical patterns and features, which leads to the development of tacit knowledge. This kind of learning is a ubiquitous, robust phenomenon that likely occurs in most, if not all, tasks in which individuals engage throughout their lives. In this paper, we argue that implicit learning and its end state, tacit knowledge, may assist in the acquisition, retention, and transfer of expertise and thus provide a form of *tacit scaffolding* for expertise development. The notion of tacit scaffolding represents a novel and interesting area of future research for the field of naturalistic decision making and naturalistic cognition.

## Introduction

As people go about their lives each day, they encounter a wide range of dynamic situations. These situations may come to us in the form of traveling to and from work, interacting socially with other individuals, and surviving events that may harm us. These kinds of dynamic situations produce temporal correlations across scenes that may be *implicitly learned,* in the sense that the learning occurs largely without the explicit intention to learn, without full awareness of what has been learned, and in many cases without feedback from the environment to guide the learning process (e.g., Aslin, Saffran, & Newport, 1998; Cleeremans, Destrebecqz, & Boyer, 1998; Fiser & Aslin, 2001, 2002; Perruchet & Pacton, 2006; Reber, 1989).

This phenomenon of implicit learning is a relatively primitive ability that is very robust. For example, it underlies the acquisition of sensitivity to spatial and temporal pattern and structure in a number of domains, such as sensitivity to the segmentation of auditory information into wordlike units (Aslin et al., 1998; Perruchet & Vinter, 1998), second-language learning (Michas & Berry, 1994), artificial grammar (e.g., Reber, 1967), musical structures (Salidis, 2001; Tillman, Bharucha, & Bigand, 2000), and the order of objects and events in a synthetic immersive environment (Patterson, Pierce, Bell, Andrews, & Winterbottom, 2009).

In the present paper, we argue that a novel approach to the design of learning environments may be to employ implicit learning for bolstering the acquisition,

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retention, and transfer of more complex forms of knowledge, such as the development of expertise in a number of content domains. Specifically, we suggest that implicit learning is likely to occur in parallel with other kinds of (explicit) learning, and thus implicit learning is a phenomenon that could be exploited and harnessed for the purpose of improving and reinforcing the development of expertise. Moreover, we suggest that the use of immersive environments for simulation would be an ideal method for inducing and enhancing implicit learning. Thus, implicit learning represents a novel and interesting area of future study for the field of naturalistic decision making and naturalistic cognition.

We should point out up front that the major issues of how implicit learning can be harnessed, and how training regimes for implicit learning should be developed, remain a significant challenge. At this point in scientific process we do not have solutions to these perplexing problems. We simply raise these issues in an effort to announce new possibilities in the field of naturalistic cognition.

Because implicit learning involves the unintentional, and largely unconscious, learning of dynamical statistical patterns and features in the environment, we begin our coverage of implicit learning by first discussing how well individuals can learn statistical information from the environment. Surprisingly, this topic, which was originally discussed in what has been called the "heuristics and biases" literature, has been quite controversial.

## Heuristics and Biases

Over the past several decades, it has been claimed that humans may not be very good at making decisions based on beliefs about the probability of uncertain events (Tversky & Kahneman, 1974). Specifically, there is evidence that humans ignore, or underestimate, prior probabilities and base rates when making judgments of subjective probabilities. These errors in reasoning and decision making seem to arise from the reliance upon shortcuts or heuristics.

This emphasis on poor decision making began with several seminal publications by Kahneman and Tversky in the 1970s (Kahneman & Tversky, 1972, 1973, 1979; Tversky & Kahneman, 1971, 1973). In their summary article, Tversky and Kahneman (1974) described several heuristics that humans typically use when making probabilistic decisions under uncertainty: *representativeness* (assessing the probability of an event based on its similarity to a category or population); *availability* (assessing the probability of an event based on the ease with which instances of the event can be recalled); and *anchoring and adjustment* (assessing the probability of an event by taking a suggested value and insufficiently adjusting it upward or downward to account for new information). It is important to note that the standards adopted by Kahneman and Tversky to judge whether human decision making was rational involved the application of statistical norms, such as whether or not base rates and prior probabilities were taken into account.

Based on their assessment of the use of such heuristics, Tversky and Kahneman (1974) referred to human judgments of probability as basically flawed and leading to "serious errors," "predictable biases," "systematic errors," and "fallacies." In what is perhaps the strongest statement made in their 1974 article, Tversky and Kahneman stated, "What is perhaps surprising is the failure of people to infer from lifelong experience such fundamental statistical rules. . . . Statistical principles are not learned from everyday experience" (p. 1130). This view, that humans are poor decision makers because of their reliance on heuristics, has persisted up to present day in the mainstream psychological literature (e.g., Kahneman & Frederick, 2002; Milkman, Chugh, & Bazerman, 2009). For example, Milkman et al. stated, "Unfortunately, we have little understanding of how to help people overcome their many biases and behave optimally" (p. 379).

These claims have been criticized on a number of points. In particular, it has been argued that this research has (a) lacked generalizability and relevance for real-world decision making (Lopes, 1991); (b) imposed statistical norms without taking into account the content of the problem or situation (Einhorn & Hogarth, 1981; Gigerenzer, 1996; Lopes & Oden, 1991; see also Kahneman & Tversky, 1996); (c) presented heuristics that were too vague to count as explanations (Gigerenzer, 1996); (d) taken probability theory as a norm for single events (i.e., Bayesian), which would be considered misguided by many statisticians, who hold that probability theory concerns repeated events (Gigerenzer, 1994; see also Lopes, 1981); and (e) inappropriately used simple probability models as norms in situations calling for induction (Lopes, 1982).

It is important to note that the claim that judgments of probability are flawed depends upon the way in which the problem or situation is presented. It has been reported that judgments come closer to conforming to Bayesian principles when numerical information about base rates and prior probabilities is presented as raw frequencies (Cosmides & Tooby, 1996; Gigerenzer & Hoffrage, 1995; Tversky & Kahneman, 1983). Gigerenzer and Hoffrage argued that the reason a raw-frequency format makes such a difference is that cognitive algorithms working on frequencies involve fewer mental steps. Thus, it appears that humans have great difficulty abstracting statistical information from events in their everyday lives, a difficulty that can be partially ameliorated by having such information represented as simple frequency rather than as probability.

But is this view of human decision making correct? Do humans actually have trouble learning statistical principles from everyday experience? In the discussion that follows, we argue that humans have an innate capacity to easily learn from their life experiences statistical principles such as joint probability and conditional probability and that they do so without intention, instruction, or feedback—they learn such principles implicitly.

# Implicit Learning

*Implicit learning* refers to the process of learning without intention and without being able to verbalize easily what has been learned (e.g., Aslin et al., 1998; Cleeremans et al., 1998; Fiser & Aslin, 2001, 2002; Mathews et al., 1989; Perruchet & Pacton, 2006; Reber, 1967, 1989; Reber, Kassin, Lewis, & Cantor, 1980). In the seminal work on implicit learning, Reber (e.g., 1967) had participants memorize strings of letters that were derived from an artificial grammar created from a finite state algorithm. Each letter string looked like a random sequence, yet the set of letter sequences taken from the grammar possessed a subtle statistical structure. Following learning, the participants could reliably discriminate novel letter strings created from the grammar from actual random strings, even though they could not verbalize much about the structure of the grammar (Mathews et al., 1989; Reber, 1967).

Recent analyses suggest that individuals learn certain aspects of the underlying statistical patterns as well as chunks of stimulus features in implicit learning experiments (for review, see Perruchet & Pacton, 2006). Other work on implicit learning has involved motor sequence learning and dynamic system control (for review, see Cleeremans et al., 1998). The existence of knowledge that is difficult to verbalize is consistent with the concept of tacit knowledge as discussed by Polanyi (1966), who argued that there exists a form of knowledge that is difficult to express in propositional form.

Recent research by Aslin and colleagues and Turk-Browne and colleagues (Aslin et al., 1998; Fiser & Aslin, 2001, 2002; Saffran, Aslin, & Newport, 1996; Turk-Browne, Junge, & Scholl, 2005; Turk-Browne, Scholl, Chun, & Johnson, 2009) has shown convincingly that the implicit learning of statistical patterns can be unintentional and can occur without feedback guiding the learning process; these authors called this kind of learning "unsupervised." These authors have found that individuals can implicitly learn a range of statistics dynamically, such as raw frequencies, joint probabilities, and conditional probabilities. The results from this line of research showed that previous claims made in the heuristics and biases literature, that humans have trouble learning statistical principles, was patently wrong. Humans certainly possess this ability; it is simply difficult for them to verbalize the fruits of that ability.

Based on the foregoing discussion, we suggest that humans possess a natural capability for learning and remembering statistical patterns from their environment, but it is difficult for much of that information to penetrate conscious awareness—it is implicit or tacit. This idea is similar to the notion by Lockhart and Blackburn (1993) of *conceptual access* as a source of difficulty during problem solving. Specifically, these authors made a distinction between two types of difficulty when a person is implicitly solving a problem: (a) difficulty with problems requiring extensive construction and application of procedures, and (b) difficulty with problems requiring retrieval and activation of existing cognitive representations.

According to these authors, the latter difficulty is one of conceptual access, which arises whenever an existing set of cognitive procedures resides in long-term memory and the issue is one of retrieval. Pothos (2007) similarly argued that implicit knowledge is knowledge that is not consciously activated at the time of a cognitive operation. On this point, it may be that the ability to explicitly verbalize information has a higher threshold than the ability to learn dynamical statistical patterns from the environment. The higher threshold for verbalization relative to the learning of statistical patterns would mean that the statistical patterns can be learned without the ability to be fully verbalized.

In the original studies by Tversky and Kahneman (e.g., Kahneman & Tversky, 1979; Tversky & Kahneman, 1974), as well as those by other researchers in the heuristics and biases literature discussed previously, subjective estimates of the probability of uncertain events were typically obtained from the participants, which meant that these studies involved assaying the participants' statistical knowledge at a conscious level, knowledge about which the participants seemingly lacked sufficient conceptual access. Apparently, changing the context and presenting the problems in a frequency format (Cosmides & Tooby, 1996; Gigerenzer & Hoffrage, 1995) permitted a greater amount of conceptual access. That statistical knowledge is indeed processed and retained by humans, albeit tacitly, is revealed in the implicit learning studies by Aslin and colleagues discussed previously (Aslin et al., 1998; Fiser & Aslin, 2001, 2002).

## Expertise Development Through Tacit Scaffolding

Given that statistical learning can occur implicitly—that is, without intention and without feedback (Aslin et al., 1998; Fiser & Aslin, 2001, 2002)—it seems reasonable to conjecture that this kind of learning occurs in parallel with the learning of more complex forms of knowledge, such as when individuals attempt to acquire a high level of expertise and skill in a given content domain. Evidence supporting this idea comes from Berry and Broadbent (1984, 1988), who reported that the ability of individuals to control different interactive computer-implemented tasks (e.g., control the output of a sugar-production factory by varying the number of workers employed) was developed implicitly when the underlying relationship between the tasks' input and output variables was subtle, but the individuals' ability to control the tasks could be made explicit when the underlying relationship between the variables was salient.

In many situations, a high level of skill is needed to perform certain tasks in complex work environments, such as piloting a fighter aircraft. The development of such skill will typically take many years to achieve proficiency (e.g., Ericsson, 2006). Moreover, in certain cases an individual may need to leave a given work assignment and go to another job or position, thus functioning in a very different domain, only to reenter the original work context and be expected to have retained the original expertise and skill. However, during the tenure at the new assignment, there is typically little opportunity to train or practice the skills required at the original assignment to which the individual will eventually return. These issues involve the acquisition, retention, and transfer of expertise (for discussion of expertise, see Hoffman, 1996; Hoffman, Feltovich, Fiore, Klein, & Ziebell, 2009).

In the following discussion, *implicit learning* will be defined as a largely unconscious process for acquiring and developing different kinds of skills, knowledge, or expertise, whereas *tacit knowledge* (Polanyi, 1966) will refer to an end state. Intuitive decision making, discussed later within the context of naturalistic decision making and the recognition-primed decision model, will refer to a situational pattern recognition process based on tacit knowledge developed through implicit learning.

Given the difficulty in developing, retaining, and transferring expertise, it comes as no surprise that there have been significant efforts to understand how this can be accomplished (Feltovich, Coulson, Spiro, & Dawson-Saunders, 1992; Hoffman & Militello, 2009; Lajoie, 2003). For example, suggestions for accelerating the transition from student to expert have included the idea of presenting to the learner a trajectory plot showing the path toward expertise (Lajoie, 2003). Retention of knowledge and skill can be improved when material at the time of acquisition is elaborated and integrated with other knowledge (e.g., Bransford, Brown, & Cocking, 2000) and cognitive flexibility is developed (Spiro, Coulson, Feltovich, & Anderson, 1988). Finally, methods of instruction based on cognitive transformation theory (which focuses on correcting flawed mental models rather than on filling gaps in knowledge; Klein & Baxter, 2009) and cognitive flexibility theory (which focuses on multiple knowledge representations for promoting knowledge transfer; Spiro et al., 1988) are focused on promoting the development of appropriate conceptions as well as correcting faulty ones.

In addition to these kinds of explicit efforts made to master a given set of skills and develop expertise, there are also likely to be implicit processes, operating in parallel and without intention and with less than full awareness, that could lead to the development of tacit knowledge and support the more explicit kinds of learning (e.g., Perruchet, Chambaron, & Ferrel-Chapus, 2003). For example, when weather forecasting, are the forecasters relying upon tacit knowledge of the spatiotemporal correlations of cues and patterns in the unfolding weather pattern in addition to their explicit knowledge of physics? Could the activation of tacit knowledge gained through implicit learning actually serve to enhance the acquisition, retention, and transfer of more complex, explicit skills and knowledge that underlie expertise? In other words, could there exist a kind of *tacit scaffolding* that could be optimized through certain kinds of training regimes? We believe that this is an important, yet neglected, possibility.

The possibility of developing a tacit scaffolding for supporting the acquisition, retention, and transfer of expertise addresses, at least in part, a problem we see in exclusively using subject matter experts as a means for training novices. The problem in exclusively using subject matter experts for training is that they will typically know more than they can verbalize to another individual—much of their knowledge would be tacit (e.g., Polanyi, 1966). One potential remedy for this problem would be to employ implicit learning techniques in the training in order to develop tacit knowledge.

One method for inducing implicit learning, which would create tacit scaffolding for use in the enhancement of the acquisition, retention, and transfer of expertise, would be the use of immersive environments for simulation. This topic is discussed in the following section.

## Naturalistic Decision Making

Tacit knowledge gained through implicit learning is thought to provide, in part, the basis for intuitive reasoning and decision making (e.g., Evans, 2008; Hogarth, 2001; Reber, 1989, 1993). Intuitive decision making refers to decision making based on holistic, perceptual, situational pattern recognition (Evans, 2003, 2008; Hammond, 2007; Hogarth, 2001, 2002; Kahneman & Frederick, 2002; Kahneman & Klein, 2009; Klein, 1998, 2008; Sloman, 1996). Reber (1989), for example, has argued that the process of implicit learning is needed to create the basis for intuition and tacit knowledge.

Indeed, the concepts of implicit learning and tacit knowledge have been around since the beginning of the field of naturalistic decision making (NDM) 20 years ago. At that time, Klein (1989) proposed a model of intuitive decision making called the recognition-primed decision (RPD) model. This model posited that individuals made decisions by matching a current situation to a composite mental representation of past experiences, which then determined a given course of action.

This model, and its empirical underpinnings, were elaborated in a later book by Klein (1998). In that book, Klein discussed the results of field research he performed involving fireground commanders, which helped give rise to the initial RPD model. Klein had a fireground commander relate the following story:

> It is a simple house fire in a one-story house in a residential neighborhood. The fire is in the back, in the kitchen area. The lieutenant leads his hose crew into the building . . . to spray water on the fire, but the fire just roars back at them. “Odd,” he thinks. The water should have more of an impact. They try dousing it again, and get the same results. They retreat a few steps to regroup. Then the lieutenant starts to feel as if something is not right. He doesn’t have any clues; he just doesn’t feel right about being in that house, so he orders his men out of the building. . . . As soon as his men leave the building, the floor where they had been standing collapses . . . they would have plunged into the fire below. (Klein, 1998, p. 32)

The fireground commander in this situation had believed that his “extrasensory perception (ESP) had saved the day.” But upon further close questioning, the commander realized that his expectations had been violated, which is why he ordered his men out of the building: There was no suspicion of a fire in the basement (which is where it actually was); the living room of the house was hotter than expected for a fire in the kitchen (because the fire was in the basement); and it was too quiet for so much heat (because the floor muffled its sound). This is a prime example of tacit knowledge: knowledge that is difficult to verbalize (Polanyi, 1966). Klein (1998) provided a number of other examples from his field research showing that implicit learning and tacit knowledge were key components of intuitive reasoning and decision making.

Thus, we believe that implicit learning and tacit knowledge provide a critical foundation for cognitive processing within naturalistic contexts. It is therefore surprising that implicit learning and tacit knowledge have not received more attention from the NDM community. For example, there were two very interesting presentations, among others, at the recent NDM9 conference in London, UK. In one, Baber (2009) presented a paper on using head-worn computers for assistance in the examination of crime scenes. The author concluded that wearable computers can enhance crime scene examination by integrating tasks involving search, retrieval, and recording of evidence in a way that that is not possible with typical laptop computers. In another presentation, Greitzer, Podmore, Robinson, and Ey (2009) described a naturalistic decision-making model for power system operators that involved taking transcripts of conversations. These authors found that an NDM approach provided a viable framework for accelerating learning in simulator-based training scenarios.

In these and other interesting papers at the NDM9 conference, there was no apparent mention or analysis of implicit learning or tacit knowledge. This was true even though it would be likely that when examining a crime scene, or when assessing the status of a power system grid, the individuals involved would be relying, in part, upon tacit knowledge of implicitly learned dynamic cues and patterns in the unfolding situation, in addition to their explicit knowledge of the phenomena.

## Training Tacit Skills and Knowledge

There is evidence that implicit processing can enhance learning, but this enhancement appears to be moderated by other factors, such as the type of material being learned and expertise level. For example, Mathews et al. (1989) reported that implicit processing was sufficient for the learning of correlated artificial letter sequences but was inadequate for learning sequences based on logical rules. A synergistic learning effect occurred when both implicit and explicit processing was used with the letter sequences based on logical rules. Pretz (2008) investigated the ability of college students to solve everyday problems and found that an implicit perspective was appropriate for novices whereas an explicit analysis was appropriate for more experienced individuals. Sun, Slusarz, and Terry (2005) investigated implicit and explicit processes in skill learning and argued for an integrated model that entailed a bottom-up approach (first learning implicit knowledge and then explicit knowledge). However, Reber et al. (1980) reported that the optimum training mode was to have individuals explicitly learn information about the structure of the material and then observe and analyze an extended series of exemplars generated by it.

Patterson et al. (2009) found that individual differences also play a significant role in implicit learning and tacit knowledge. In their study, participants were passively exposed, during training, to a series of structured object sequences viewed during simulated locomotion through an immersive environment.

Following training, the participants were tested for tacit knowledge by having them identify novel structured sequences versus random sequences (learning was largely implicit because participants could not verbalize fully the basis on which they made their identifications). The results showed that 3 of 7 participants approached or reached a criterion level of 90% correct following the first training session, whereas the 4 other participants took multiple training sessions to reach criterion (2 of whom were at or near chance level at the end of the first session). Such individual differences in learning were related, in part, to explicit rule induction—the slower participants were generating explicit rules for the object sequences that were incorrect. When these participants ceased doing so, their learning increased.

If the enhancement of tacit knowledge could serve to bolster the acquisition, retention, and transfer of more complex skills and knowledge that underlie expertise, then the question arises as to how to train for the development of such knowledge. In a paper that reviewed the literature on analytical decision making, intuitive decision making, and working memory, Patterson et al. (2009) suggested that immersive environments should be an important tool for inducing implicit learning and thus the training of intuitive decision making. (Note that these authors did not discuss the idea that statistical knowledge is retained at a tacit level and did not mention the idea of conceptual access; nor did they introduce the concept of tacit scaffolding.) These ideas were based, in part, on an analysis by Hammond, Hamm, Grassia, and Pearson (1997).

Hammond et al. (1997) proposed the existence of a cognitive continuum, with analytic decision making at one end and intuitive decision making at the other end ("quasi-rational" decision making referred to a blend of the two types of reasoning and was positioned in the middle of the continuum). Moreover, these authors also suggested the existence of a task continuum that corresponded with the cognitive continuum. Thus, at one end of the task continuum, an analytic-inducing task would entail deliberative judgments involving symbols (e.g., language; mathematical expressions) and few cues that would be based on rules or algorithms. At the other end of the task continuum, an intuitive-inducing task would entail speeded judgments about perceptual material with multiple cues and no symbolic calculation.

The term *immersive environment* refers to an environment that creates perceptual and cognitive immersion by stimulating the sensory organs directly with relevant stimulation and relevant cognitive content; such environments involve more than simply creating a stimulating situation (see Bjork & Holopainen, 2004, p. 423). An immersive environment would be ideal for presenting perceptual material involving multiple cues, and thus it should be ideal for inducing implicit learning and the training of intuitive decision making (Patterson et al., 2009). Accordingly, immersive environments may also be an important tool for enhancing the acquisition, retention, and transfer of high-level expertise.

Although the use of such devices in training has become routine in a wide variety of domains (e.g., Andrews & Bell, 2000; Mitchell & Flin, 2007), their use has not emphasized implicit learning of expertise or tacit scaffolding. In many applications, the simulation training emphasizes the synthetic creation and practice of real-world events. We propose instead a training approach that would involve the definition of key exemplars necessary for naturalistic decision making in a particular domain, the identification of multimodal cues necessary for synthetically replicating those exemplars, and the development of effective methodologies for providing the trainee the necessary experiences.

To do so, training for the development of expertise in a given domain could entail creating conditions in an immersive environment that promotes the implicit learning of selected exemplar situations or scenarios. Toward this end, future research should be directed toward understanding the key principles that optimize implicit learning and the development of tacit knowledge in immersive environments and, thus, precisely how to structure the delivery of the exemplars and scenarios. This is important because the training would need to be structured so as to avoid confusion. However, whereas it would seem that proper training would require a great many trials, not only to present the stimuli but also to represent the variability, Patterson et al. (2009) have reported that significant learning and retention of simple classes of exemplars (i.e., sequences of objects positioned on a ground plane) can occur when only 120 exemplars are presented during training.

Of course, simulation training for the development of expertise in the real world would involve more complicated exemplars and scenarios and thus would likely entail exposure to more of them. However, it seems that implicit learning and the development of tacit knowledge is a relatively robust process. Some of the advantages of simulation training include lower cost, the ability to present unusual and/or dangerous situations to trainees, and an enhanced level of control of conditions, as compared with real-life training situations.

The development of proper implicit learning regimes for such training could be an important approach that complements the solicitation of information from subject matter experts. However, a problem remains: If the knowledge dealt with is tacit, then how are training developers going to elicit and represent this knowledge? Moreover, how can training developers assess tacit knowledge? The study of tacit knowledge elicitation, representation, and assessment should not only uncover methods for exemplar development but may also lead to the identification of new technology support tools that could play a significant role in key decision-making applications. For example, one possibility could be the creation of training systems based on visual (e.g., video) capabilities derived from surveillance activities and thus would not rely upon human verbalization. To our way of thinking, these remain the most significant issues to be confronted, and future work should be directed to resolving them.

Thus, although we would like to present in this paper a set of training principles for the development of tacit knowledge (i.e., tacit scaffolding) that could serve to bolster the acquisition, retention, and transfer of more complex skills and knowledge that underlie expertise, there is as yet too little research on which to base such principles. Whereas some of the studies discussed previously may suggest several principles, such as minimizing erroneous explicit rule induction, those studies involved very simple stimuli and conditions. It remains to be determined by future research what a reasonable and sufficient set of principles would actually look like.

## Concluding Remarks

Implicit learning and the development of tacit knowledge, which entails the largely unconscious learning of dynamic statistical patterns and features, is a ubiquitous, robust phenomenon that likely occurs in most, if not all, tasks in which individuals engage throughout their lives. Thus, implicit learning is likely to occur, in parallel fashion, when individuals develop expertise in a given content domain. This invites the speculation that the enhancement of implicit learning and tacit knowledge development may assist in the acquisition, retention, and transfer of expertise and thus provide a form of tacit scaffolding for expertise development. One technique for creating this tacit scaffolding would be the use of immersive environments for simulation. The notion of tacit scaffolding represents a novel and interesting area of future research for the field of naturalistic cognition.

As has been noted earlier, the major issues of how implicit learning and the development of tacit knowledge can be harnessed, and how training regimes should be developed, remain a significant challenge. We have presented these issues, which entail significant practical issues that await resolution, in an effort to offer new possibilities in the field of naturalistic cognition.

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