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Flexibility of knowledge as a function of practice and explicit instruction

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FLEXIBILITY OF KNOWLEDGE AS A FUNCTION
OF PRACTICE AND EXPLICIT INSTRUCTION

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
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The Department of Psychology

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ABSTRACT

Two experiments used a dynamic control task (Berry & Broadbent, 1984) to examine the flexibility of experientially acquired knowledge. The results suggest that experientially acquired knowledge of this task is represented by a lookup table, not a set of tuned strategies. With practice, transfer to a new task was achieved through an extrapolation procedure. Experiment 2 demonstrated far superior task and transfer performance in participants trained with a combination of experiential practice and model-based knowledge. Transfer to new states was only possible when participants were provided with model-based knowledge through direct instruction. Also, providing model-based knowledge during practice resulted in a more flexible representation compared to providing it before or after practice. Pedagogical implications are discussed.

INTRODUCTION

A major goal of education is not only to teach content knowledge, but to teach content in a way which allows learners to transfer that knowledge to a variety of situations (Perkins & Salomon, 1992). For example, medical students who learn about a disease in one case study are expected to recognize similar symptoms in a wide range of patients. Similarly, pilots who learn to fly in small, single-engine planes are eventually able to transfer their knowledge of aviation to larger, more complex planes in a variety of flight conditions.

Research suggests human learning is achieved through two separate, but complimentary processes; *experience-* and *model-based processing* (Anderson, 1982; Berry & Dienes, 1993; Mathews et al., 1989; Reber, 1993, for a single process theory, see Shanks & St. John, 1994). In these two-process models, model-based processing involves the intentional use of a concrete representation, or a mental model of the task such as a set of instructions or a recipe to guide performance (Johnson-Laird, 1982). Experience-based knowledge, on the other hand, is acquired without intention, through direct interaction with the environment. An example of experience-based learning is a young child acquiring language. Children learn to communicate grammatically without direct instruction through their interaction with others who speak the language (Dienes, Broadbent, & Berry, 1991).

While many researchers agree that knowledge is acquired through these two processes, the specific details of each process are debated. One particular area of debate is the flexibility of experientially acquired knowledge. This is particularly important as it pertains to training in some professional fields, such as medicine or

aviation, where practitioners are expected to apply knowledge learned through experience to mission critical decisions to new situations. Some theories propose that experientially acquired knowledge becomes rigidly tied to the task context in such a way that transfer is unlikely (Dienes & Fahey, 1995, 1998). Others suggest that in some sense, general rules or strategies are learned which may transfer to new task constraints (Lane, Mathews, Sallas, Prattini & Sun, 2007). These theories are discussed below.

An example of a task that can be learned through experiential practice will help elucidate this debate. The *dynamic control task*, developed by Berry and Broadbent (1984), has been used by a number of researchers (e.g. Dienes & Fahey, 1995; Lane, et al., in press; Marescaux, Luc, & Karnas, 1989; McGeorge & Burton, 1989; and Stanley, et al., 1989). In this paradigm, participants control the output of a system by varying the input, where the system is governed by some formula unknown to the subject. In one version of the task, participants are told they will play the role of a sugar factory manager, where the input is the number of workers and the output is production in tons of sugar (Berry & Broadbent, 1984). Their “job” is to maintain sugar production at some prescribed level. The system’s output is governed by a formula such as: $P = 20W - P_{tr-1} + N$, where sugar production is P , the number of workers entered is W , the system’s output, or sugar production, on the previous trial is P_{tr-1} , and N is a noise function which randomly adds 1000, -1000, or 0 with equal probability to the output. Inputs range in hundreds from 100 to 1200 and outputs range in thousands from 1000 to 12000. For any given previous output, there is an input that will allow the system to reach within 1000 tons of the goal state. For example, if the goal state were 6000 tons

of sugar, the correct input when the previous output is 12000 tons of sugar is 900 workers (e.g. $P = (20 \times 900) - 12000 + N$). Production values which fall above or below the range of outputs are set to 12000 or 1000 respectively.

Lane, et al. (2007) argued that while this task may seem rather simple, it functions in a way that makes it analogous to learning in the real world. First, the task is dynamic, meaning that the state of the system changes with each input. Additionally, the system is noisy such the same input can lead to multiple outputs. Third, performance on the task improves with high levels of practice, but participants' ability to verbalize their performance lags behind actual task performance (Stanley, et al., 1989). One example that shows how this task parallels real world learning is that of an educator teaching students. Teaching is a dynamic task, in that a given strategy may work well with students at one point in the school year, and not in another. Thus, teachers must base their behavior on the current state of their students. Also, teachers receive noisy feedback. A strategy that worked well with some students may fail with others. Finally, becoming a highly effective teacher can take years to accomplish, and even then, it can be difficult for expert teachers to describe their behavior.

While researchers agree that knowledge can be acquired through experiential practice with a dynamic control task, there is debate over whether knowledge gained through experience is stored as an inflexible set of specific instances or flexible, general rules. In the case of the dynamic control task, researchers disagree over whether participants store a lookup table of specific output-input pairs (e.g. if the output is 12000 tons of sugar, input 900 workers), or learn general rules or strategies (e.g. input a number between the previous output and the goal state).

One specific instance model was proposed by Dienes and Fahey (1995, 1997; see also Berry & Broadbent, 1984; Marescaux, Luc, & Karnas, 1989). In this model, Dienes and Fahey argue that participants develop a lookup table of correct output-input pairs as they interact with the task. Anytime the goal state is reached (plus or minus 1000 tons), participants are said to store the correct action for that particular output. Future responses to “old-correct” outputs are made by recalling the correct response based on a match between the current output and a stored output. Outputs which were experienced before but a correct response was not made can be called old-incorrect. Thus we can distinguish three types of trials: old-correct, old-incorrect, and new situations (never experienced before). In this model, responses to situations without a stored correct answer are determined via the application of explicit strategy (e.g. if sugar production is below target, increase workers). In a similar model, these responses are determined at random (see Cleeremans’ model, described in Marescaux, Luc & Karnas, 1989). Dienes and Fahey provided evidence for their model by demonstrating that at test (following 80 training trials), participants respond above chance only to old-correct output states indicating very little transfer to other (old-incorrect or new) states. Furthermore, participants were more consistent in how they responded to old-correct states than to other states. This pattern of results is consistent with the storage of specific output-input pairs. If participants had developed a set of general rules for responding, one would expect similar performance across all outputs. Instead, a lookup table model would predict correct performance only for those outputs for which a correct output-input pair had been stored (old-correct).

Dienes and Fahey (1995, 1997) argue that this knowledge is acquired implicitly, or without intention. While participants responded above baseline to old-correct states, this superior performance was independent of being able to recognize situations as old. In addition, Dienes and Fahey cite previous research with the dynamic control task which demonstrated that instructing participants to look for rules resulted in poor performance (Berry & Broadbent, 1998). Berry and Broadbent argued that because the task is implicit, attempting to learn the task in an explicit manner was detrimental to performance. In summary, Dienes and Fahey argue that participants learn the dynamic control task by developing an implicit lookup table consisting of specific correct output-input pairs (see Table 1). These output-input pairs are inflexible meaning that knowledge of specific pairs does not transfer to old-incorrect or new output states. Furthermore, if such knowledge does not generalize even across situations within the task (i.e. old-incorrect states), it could not be expected to transfer when task constraints are changed (i.e. a different goal for sugar production).

Unlike Dienes and Fahey (1995, 1997), Fum and Stocco (2003a, 2003b) argue that general strategies rather than specific output-input pairs are learned in the dynamic system task. Their theory is based on the ACT-R procedural system (Anderson & Lebiere, 1998). In this model, participants do not store specific instances, but instead performance is based on a set of strategies which are tuned according to previous performance. Fum and Stocco posit that participants possess a set of strategies before experience with the task (e.g. choose random input, repeat-choice) and these strategies are unconsciously chosen according to their expected utility. At first, strategies are randomly selected, but when a strategy results in loosely correct performance (target

plus or minus 1000 tons) its expected utility increases. Strategies that work are likely to be used in the future while unsuccessful strategies are less likely to be used.

Table 1. Simple lookup table of output-input pairs.

Output	Input
1000	400
2000	400
3000	500
4000	500
5000	600
6000	600
7000	600
8000	700
9000	700
10000	800
11000	800
12000	900

This tuning procedure might be likened to someone choosing a route to commute to work. If there are five routes to choose from, the probability that any route will be chosen on Day 1 is 0.2. However, if there is construction on the chosen route, its expected utility will decrease, and the commuter will be less likely to choose that route in the future. Conversely, if there is no traffic on the route, its expected utility will increase and the commuter will be more likely to choose that route in the future. Fum and Stocco's (2003a, 2003b) model operates using the following five strategies:

- "Choose Random": Choose a random input
- "Repeat-Choice": Choose the same input entered on the previous trial

- “Stay-On-Hit”: If the previous input was successful, repeat it. (More selective version of “Repeat-Choice”)
- “Pivot-Around-Target”: Input a value that is the same value of the target, plus or minus one
- “Jump On Middle”: Choose an input that lies midway between the previous output and the upper or lower limit

Fum and Stocco (2003a, 2003b) present data showing unsymmetrical transfer between goal outputs as evidence for their model. Like Dienes and Fahey, Fum and Stocco exposed participants to 2 blocks of 40 trials in the sugar factory task with one significant difference. In the Dienes and Fahey (1995) task, goal performance was always 6000 tons of sugar. Fum and Stocco used two goals (3000 and 9000) and manipulated whether the goal stayed the same or changed across blocks resulting in the following four groups: 3000-3000, 9000-9000, 3000-9000, and 9000-3000. The potential success of a strategy is dependent on the goal state, such that some strategies work better for specific goals, while others are superior regardless of the goal. For example, when the goal state is set to 3000 tons, the Choose Random strategy would result in an output within 1000 tons of the target on 18% of attempts. If the target was 9000 tons, the same strategy would result in near target output on only 12% of attempts. This difference is because 3000 is closer to the lower limit of 1000 than 9000 is to the upper limit of 12000. Outputs which fall below 1000 are set to the lower limit (1000 tons), and on one third of these trials, the noise function adds 1000 tons to the output, resulting in a loosely correct output. The goal of 9000 tons is not close enough to the upper limit to benefit in this manner. In terms of their model, this means that strategies which depend on the limit of the output scale work well when the goal is 3000, but not when the goal is 9000. Conversely, strategies which work when the goal

is 9000, work regardless of the goal. For example, the Stay-On-Hit strategy works equally well for either goal. Thus, in this model, when the goal is 3000, participants tune their set of strategies such that the strategies that are likely reach the goal of 3000 are selected. These strategies do not work as well when the goal is changed to 9000 and performance is expected to be poor until the strategies are re-tuned. Strategies which work when the goal is 9000 work at least as well at the goal of 3000. Thus, performance should increase when the goal changes from 9000 to 3000 as the strategies continue to be tuned with each successful trial.

Fum and Stocco's (2003a, 2003b) results revealed better performance in the 3000-3000 condition relative to the 9000-9000 condition, confirming their hypothesis that there are strategies which have a higher success probability for the goal of 3000 than for the goal of 9000. Instance based models (e.g. Dienes & Fahey, 1995) would predict no difference between performance at any goal. Secondly, when the goal changed from 3000 to 9000 performance was similar across blocks, but when the goal changed from 9000 to 3000, performance improved significantly. Fum and Stocco argue that an instance-based account is not able to explain this non-symmetric transfer between goals. If performance was based on stored instances, it should not improve when the goal changes as a lookup table is calibrated for a specific goal and would be of no use for a new goal. Thus, they argue that performance in the dynamic control task is based on the expected utility of strategies, not stored instances. In addition to arguing that instances are not stored, the strategies in this model are context independent. The model does not choose a strategy based on the previous output

(unless the previous output was successful, as in the Stay-On-Hit strategy). Only the strategy's success in the past is valued.

There is however one concern with Fum and Stocco's (2003a, 2003b) interpretation against an instance-based model. Dienes and Fahey (1995) reported a second experiment in which they varied the "salience" of the task. In the salient condition, the correct input was always 600, while in the non-salient condition the correct input was contingent on the previous output. Dienes and Fahey argued that participants in the salient condition learned partially by a lookup table and partially by learning a rule that could be applied across situations. This argument was based on data showing that while participants still performed better on old-correct states (instance-based), they were also above baseline on new states (rule-based).

It is possible that when the goal changed from 9000 to 3000, participants moved from an instance-only representation to a representation that included both a rule (always enter 200) and an instance-based representation. When the goal changed from 3000 to 9000, the representation would need to switch from a rule and instance-based representation to an instance-only based representation with a new set of output-input pairs. In this case, a subject would have developed a representation calibrated for the goal of 3000 and learned a rule that worked because the goal was near the lower limit. When the goal changed to 9000 participants needed to recalibrate their representation for the new goal, and discover that the rule no longer works. Conversely, when the goal changed from 9000 to 3000 participants' lookup table was no longer calibrated for the new goal, but they may have quickly learned a rule which lead to good performance. Non-symmetric transfer does not necessarily rule out an instance-based model. Fum

and Stocco's data could be explained by a switch from an instance-based representation to a representation comprised of both instances and a rule.

It is unclear what would cause this switch in representation. Nosofsky, Clark, and Shin (1989) found in a perceptual classification task that a rule-based model fit participants' data when they were instructed to use rules. When no rules were provided, an instance-based model best fit the data. Thus, instructing participants to use a rule can influence the type of representation participants develop. While there was no instruction to use a rule in above studies, the salience of the rule may have driven the switch between the type of representation used.

Lane, et al. (2007) added a third perspective on the representation of experientially acquired knowledge. To review, Dienes and Fahey (1995, 1997) argue that participants develop a lookup table consisting of specific output-input pairs, while in Fum and Stocco's (2003a, 2003b) model, individual instances are not stored, but a set of context-independent strategies is tuned over time such that the most successful strategies are most likely to be selected in the future. Lane, et al. suggested that participants develop an implicit lookup table as proposed by Dienes and Fahey, but argue that more general, contextually relevant rules (e.g. if the output is high, use an input of 800), rather than specific instances are stored in the lookup table. One problem with the proposal that knowledge is stored in a specific lookup table is dealing with the large volume of instances which must be stored. If participants store all experienced output-input pairs that lead to "loosely correct" outputs, at some point interference would make it difficult to store new instances or recall old ones. Lane et al.'s model is in line with Mathews' (1991) Forgetting Algorithm in which the specific features of individual

instances are lost over time and replaced with features which are common across instances.

Lane, et al. (2007) provided several pieces of data to support this claim. First, participants who learned the task through experiential practice were able to transfer their knowledge to a new goal without a drop in performance. If participants relied only on specific output-input pairs, transfer performance should have been poor as a specific lookup table is calibrated for a particular output. Like Dienes and Fahey (1995), Lane, et al. provide evidence that this knowledge is implicit by showing that performance on a fill-in-the-blank style “table test”, which required participants to write the correct input for each previous output to attain the goal state, was worse than actual performance on the actual task completed just minutes before. If participants had access to the knowledge they used to perform the task, performance should have been similar across both measures.

Lane, et al. (2007) also argued against an instance-free representation like that of Fum and Stocco (2003a, 2003b). While the Fum and Stocco’s model can account for transfer in Lane, et al.’s experiential practice condition, it cannot account for data demonstrating that providing hints to participants improved performance. In Experiment 1, Lane, et al. provided participants in a “hint” condition three correct output-input pairs. Performance on the dynamic control task was superior in participants who were provided the hints relative to participants who learned though experiential practice alone, even on output states for which no hint was provided. This suggests that instances are important to learning the dynamic control task.

Also, in Experiment 2, Lane, et al. (2007) provided participants in a “table” condition with a full, correct lookup table. Thus, before practice with the task, these participants knew how to reach the goal state from all previous states. Performance in this group was superior to the experiential practice condition. On a transfer test, where the goal changed from 6000 to 9000, participants in the table condition performed as well as those in the experiential practice condition. This suggests that through extensive practice with the task, participants in the table condition also acquired some experiential knowledge. In Fum and Stocco’s (2003a, 2003b) model, participants in the table condition would have not have the opportunity to tune a set of strategies as instead, they employed an explicit lookup table to perform the task.

Lane, et al. (2007) provided evidence that when participants receive extensive practice, knowledge is stored as somewhat more general rules rather than specific instances (e.g. if output is high, input 800). Performance on a transfer test in which the goal state was changed was compared between participants who had extensive experiential practice with the task and a control condition which had no practice, but was provided with a complete and correct look-up table to memorize before the test. A specific look-up table model would predict similar performance across the two conditions as the table provided to the control condition is presumed to be the form which experientially acquired knowledge takes. Their results showed significantly better performance on the transfer test for the experiential practice condition. In fact, the experiential practice condition exhibited similar performance on both the new goal test and standard test, where the goal was the same as training. Lane, et al. argued this superior performance over control was the result of the flexibility of more general rules

acquired through experiential practice compared to the inflexibility of a specific look-up table.

One significant difference in the methodology between Lane, et al. (2007) and the other research cited above (Dienes & Fahey 1995, 1997; Fum & Stocco, 2003a, 2003b) is amount of practice with the task that participants received. In Lane, et al., participants in the experiential practice condition of Experiment 1 interacted with the task for an average of 3410 trials, compared to 80 trials in research by Dienes and Fahey and Fum and Stocco. Both Lane, et al. and Dienes and Fahey (1998) speculate that learners with low levels of practice may represent experientially acquired knowledge in the form of a specific look-up table, which is replaced with a set of general rules with more experience. Furthermore, Fum and Stocco (2003b) suggested that storing instances may be important to learning in a dynamic control task, but not in the levels of training provided to participants in their experiments. While the idea that the representation of knowledge may change across time seems to fit the data described above, the hypothesis has not been explicitly tested within a single study, and extrapolation across studies is problematic due to several significant procedural differences beyond the number of training trials.

Another difference is that both Dienes and Fahey (1995, 1997) and Fum and Stocco (2003a, 2003b), used long blocks of trials which may have limited participants' exploration of the problem space (Newell & Simon, 1972). In these studies, each block consisted of 40 trials, with each new output dependent on the previous output and the subject's input. Thus, participants may have spent more time at one particular output level, as several inputs (100, 200, 300, 1000, 1100, and 1200) result in an output at the

lower or upper limit in most situations in which they are applied. Additionally, both Dienes and Fahey and Fum and Stocco used a procedure which always set the output to 6000 at the beginning of the block and displayed the previous input as 600. Some participants may have assumed, correctly, that they should input 600 when the output is 6000. The resulting answer would be correct, and participants would have no incentive to input any other value. Lane, et al. (2007) used blocks of ten trials and randomly chose a starting position at the beginning of each block. Thus participants were exposed to each output state multiple times in practice while those in the other studies reported here did not experience all system states. It is possible that when very few states are experienced, a look-up table is most effective representation. Conversely, when many states are experienced, a more general representation may be more effective.

Also, different cover stories have been used across studies. Dienes and Fahey (1995, 1997) and Fum and Stocco (2003a, 2003) used the Sugar Factory task described above. Lane, et al. (2007) used a nuclear reactor cover story in which participants entered fuel pellets and the system's output was reactor temperature. While it is unlikely that the cover story contributed to differences in knowledge representation, a single cover story (nuclear reactor) will be used in the proposed experiments.

Another significant difference between Lane, et al. (2007) and the research of Fum and Stocco (2003a, 2003b) and Dienes and Fahey (1995, 1997) is that Lane, et al. provided some participants with model-based knowledge about the task. Lane, et al. suggested that participants may learn best from a combination of direct instruction and

experiential practice compared to either type of instruction in isolation. Though numerous studies demonstrate that the dynamic control task can be learned through experiential practice alone (Berry & Broadbent, 1983; Dienes & Fahey, 1995, 1997; Fum & Stocco 2003a, 2003b; Stanley, 1989), participants in Lane, et al. who memorized the full look-up table before practicing the task achieved much better performance than those who learned the task through experiential practice only. However, when the goal state was changed on a new goal test or response time was limited on a speeded test, performance suffered in participants who received both model-based knowledge and experiential practice, falling to levels similar to the experiential practice only condition (but still significantly better than a no practice control condition). Lane, et al. argued that participants who memorized the table before practice also acquired experiential knowledge through practice with the system. Thus when the system parameters changed, making it difficult to use their model-based knowledge, they reverted to their less precise experiential knowledge. Lane, et al. claim that participants in the table condition must have acquired a similar level of experiential knowledge as those participants in the experiential practice condition. However, it is possible that participants who memorized the table may not have developed as much experiential knowledge as those in the practice-only condition. Because participants in the table condition knew the correct input for each output, there was no need for them to explore the problem space and develop additional knowledge. The relatively poor performance on the new goal and speeded tests may have been the result of not exploring the problem space. If participants followed the look-up table, they would reach the target after the first trial of each block, and noise would move the output between 5000-7000.

Thus, participants would need to recall the input for one of those three outputs on nine of every ten trials. Additionally, 25% of the first trials of each block would begin on one of those numbers (5000, 6000, or 7000), meaning that if participants exclusively followed the table, they would recall the input (600) for those three outputs more than nine times as often as the other inputs combined.

Secondly, data from Lane, et al. (2007) suggest that model-based knowledge can be transferred without any experiential practice. Two control groups were run with both groups taking the transfer test (9000 goal) with no prior experience with the task. One of the groups memorized a table with the output-input pairs calibrated for the standard test goal (6000 goal). While not a significant effect, participants who memorized the table performed nominally better than those without the table ($p = .07$). Both the experiential practice and table plus practice conditions outperformed both of the control conditions on the new goal test, demonstrating that model-based knowledge alone does not transfer to a new goal as well as model-based knowledge combined with experiential practice. However, that model-based knowledge alone does seem to transfer slightly better than no knowledge at all could be evidence that participants in the table condition were not only relying on experientially acquired knowledge during the transfer test. Thus, while Lane, et al. (2007) demonstrate that providing model-based knowledge along with experiential practice improves task performance and transfer, it is possible that the provision of model-based knowledge before practice reduces participants' exploration of the problem space resulting in superior performance for only some output states. The implication of this is that providing model-based knowledge before practice may reduce the amount of experientially acquired knowledge. By

delaying the point at which model-based knowledge is provided it may be possible to increase participants' acquisition of experiential knowledge. This, in turn, may reduce the decline in performance when the goal is changed or the response time is limited associated with the provision of model-based knowledge found by Lane, et al.

The first goal of the current experiments is to study the flexibility of experientially acquired knowledge as a function of length of practice. Experiment 1 will test the speculation of both Dienes and Fahey (1995) and Lane, et al. (2007) that with little practice, participants represent experientially acquired knowledge as a lookup table which is rigidly tied to the task context and unlikely to transfer, and that with more practice knowledge is represented as general rules which are still valid when the task constraints change.

Of course, not all learning occurs experientially. Some knowledge is acquired via direct instruction or a combination of direct instruction and experiential practice. From Lane, et al. (2007), it is clear that participants who received model-based knowledge outperformed those who only acquired experiential knowledge, but the model-based knowledge group was not able to transfer their knowledge as well as the experiential practice group. So while instructing learners with model-based knowledge may lead to strong task performance, there is a cost in terms of transfer to a new goal associated with direct instruction. Experiment 2 will examine the hypothesis that allowing participants to practice the task before providing them with model-based knowledge will allow participants to develop a flexible representation which can transfer when the task constraints change and also acquire very accurate task-specific knowledge.

EXPERIMENT 1

Participants in experiment 1 were assigned to 1 of 2 conditions, which differed only in the amount of training on the process control task. Those in the short training condition completed 14 blocks, with each block consisting of six trials. This resulted in slightly (84 vs. 80) more trials than participants in Dienes and Fahey (1995, 1997) and Fum and Stocco (2003a, 2003b) experienced. However, the previous output for the first trial of each block was selected using a random without replacement selection procedure, such that each output state was seen at least once across the 84 trials. Unlike previous research using long blocks, this ensured that participants were exposed to the entire problem space. Participants in the long training condition completed 280 blocks (1680 trials), or 20 times the amount of practice in the short training condition.

After a short or long training phase, participants took a series of tests. The first test was similar to the training phase, except that the range of outputs were extended from 1000-12000 to -3000-16000. Additionally, after selecting a response, participants were required to place a wager on the outcome of their response as a measure of confidence in their decision (Persaud, McLeod, & Cowey, 2007). Following the extended range test, participants took a new goal test, as in Lane, et al. (2007) in which the goal output was 8000 rather than 6000. Finally, also like Lane, et al., participants completed a table test. Here, participants were asked a series of questions about the correct input for each previous output (e.g. If the reactor's temperature is 12000 degrees, how many fuel pellets should you enter to move the temperature to 6000 degrees).

This procedure allowed for the testing of multiple hypotheses. The first hypothesis is that with little training, participants represent knowledge acquired through experiential practice as a specific lookup table (Dienes & Fahey, 1995, 1997), not a set of tuned strategies (Fum & Stocco, 2003a, 2003b). A look-up table model predicts poor performance on previously unseen states while a strategy-based model would predict similar performance across both previously seen and unseen (extended range) states. In a lookup table model, if the learner has not experienced a state, they could not possibly store a condition-action link for that state. Dienes and Fahey provided evidence for this model by demonstrating that participants performed poorly at test for states which they had not seen, or had not entered a loosely correct input, at practice. By extending the range, it was assured that participants encountered some output states for which they could not possibly have the correct output-input pair stored. If performance is based on a lookup table, superior performance should be expected on old-correct output states.

If participants tuned a set of strategies during training (Fum & Stocco 2003a, 2003b), performance should be consistent across all states on the Extended-Range Test. Any strategy tuned to reach the goal of 6000 in practice, where the range is 1000-12000, will work equally as well when the range is extended. The goal of 6000 is not near enough to the upper or lower limit in the standard or extended range to benefit from the limit as the goal of 3000 did in Fum and Stocco. Thus, if participants use a set of tuned strategies to perform the task, no difference in performance should be expected across output states in the standard and extended range.

One criticism of this analysis might be that subject could possibly have a lookup table and use some extrapolation procedure to “fill in” missing cells in the table. In the proposed experiment, reaction times will be measured. It is reasonable to assume that recalling an output-input pair will take significantly less time than calculating the correct input based on known output-input pairs. Thus if participants extrapolate missing output-input pairs based on their current lookup table, the data should show similar performance on old-correct compared to new and old-incorrect outputs, as participants should be able to “work out” the correct answer. Also, participants should take longer to respond to new and old-incorrect outputs, as the extrapolation procedure should come at a time cost over simply recalling a stored output-input pair. It is not expected that the results will suggest such extrapolation, as Dienes and Fahey (1995) found on their specific situation test that participants responded correctly to new items less than 10% of the time compared to 32% for old-correct items. If an extrapolation procedure was being used, one would expect above chance performance on these new states. That responses on new states were at chance is not indicative of an extrapolation strategy.

The second hypothesis is that with high levels of training, participants’ representation of experientially acquired knowledge changes from a specific lookup table to a set of contextually relevant rules. Dienes and Fahey (1995) show that with little training participants rarely answer correctly on items for which they had not previously answered correctly. On the other hand, Lane, et al. (2007) demonstrated that participants with extensive experiential practice do equally well on a standard and a far transfer test where the goal was changed from 6000 to 9000. In the current

experiment, both the extended range and the new goal tests required participants to transfer knowledge.

If knowledge is represented as a look-up table, performance on outputs previously answered correctly in the extended range test should be superior to unseen (extended range) outputs. Conversely, a general rules model would predict no difference across both types of items. If knowledge representation changes with practice participants with little training should show poor performance on new and old-incorrect output states, suggesting the use of a lookup table, while those in the long training condition should show similar performance across all output states, suggesting the use of a set of general rules. Again, reaction times can be used to ensure that participants are not extrapolating empty cells from a lookup table.

Similarly on the new goal test, if knowledge is stored as a lookup table, participants should show poor performance across all output states because they would not have the correct output-input pairs stored for the new goal. If knowledge were stored as flexible general rules, this knowledge should transfer to a new goal.

The extended range test was also used to test the hypothesis that with practice, participants become increasingly aware of their knowledge of the task. Many researchers argue that experientially acquired knowledge is stored implicitly, or without awareness. Berry and Broadbent (1984) reported that with low levels of practice, participants showed better than chance performance, but could not verbalize how they were performing the task. Additionally, Hayes and Broadbent (1988) found that a concurrent memory task did not harm task performance. Most models of implicit knowledge assume it is deployed automatically, and thus impervious to the demands of

other tasks (Anderson, 1983). On the other hand, Stanley, et al. (1989) asked participants to write instructions for novices at multiple points during training and found that while performance based on these instructions lagged behind the participants' actual task performance, participants were able to report some knowledge. The results of Stanley, et al. suggest that knowledge acquired experientially may at first be implicit, but that participants may become aware of at least some of this knowledge with greater experience with the task. It is important to note that using verbal reports as evidence that participants are unaware of their knowledge has been criticized (Holender, 1986; Shanks & St. John, 1994; Tunney and Shanks, 2003). Shanks and Tunney argue that participants do not report experientially acquired knowledge due to a response bias, rather than a lack of access to this knowledge. They claim that participants set their own criteria for responding, and that this criterion may be set too conservatively. Thus, they argue participants do not report awareness of knowledge even though they have some level of awareness.

Recently, Persaud, McLeod, and Cowey (2006) used a post-decision wagering procedure to demonstrate a lack of awareness of experientially acquired knowledge. Three tasks which are often used in the implicit learning literature were employed; blindsight, the Iowa gambling task, and artificial grammar learning. In each of these tasks, participants typically are able to perform the task at above chance levels, but cannot report how they make their decisions (Reber, 1967). Persaud, et al. asked participants to make either a large or small wager after each decision, but before feedback was given. If participants are aware of the knowledge they use to make decisions, they should attempt to maximize their earnings by placing large wagers after

responses they know to be correct, and small wagers following responses they are unsure of. While participants responded with greater than chance accuracy to the primary task, participants did not systematically place wagers to maximize winnings, suggesting a lack of awareness. Additionally, participants did not consistently place the minimum wager, which would have suggested the placement of a high criterion such as Shanks and Tunney have suggested. Persaud, et al. speculate that subjective measures of awareness force an introspective process, asking participants how aware they are of their awareness. Asking participants to make a wager may allow for a more precise measure of awareness due to the fact that participants need only make a binary choice (high or low wager) and can base their decision on any evidence they feel has utility.

If with low levels of practice, knowledge is stored as an implicit lookup table, participants should not demonstrate awareness through advantageous wagering. However, as Stanley, et al. (1989) reported, participants who receive high levels of training can verbalize at least some of their knowledge of the task, though verbal reports lagged behind actual task performance. As experience with the task increases, participants with more practice should be more successful at maximizing earnings, thereby demonstrating awareness of the knowledge used to perform the task. However, in line with Stanley, et al., participants in the long training condition may not exhibit perfect wagering performance as awareness may lag behind task performance.

Finally, participants will be asked to articulate their knowledge on a table test. Lane, et al. (2007) found that when asked to complete a table that asked them to write the correct input for a given output, participants who only practiced the task performed

worse on the table test than their task performance would predict. Again, Stanley, et al. (1989) suggested that participants' ability to articulate task knowledge lagged behind task performance. A similar pattern should be expected in experiment 1 such that participants with little practice should not be able to report any task knowledge, even for output states for which they have the correct input stored (old-correct). Like in Lane, et al., participants with more training should perform better than those with little training on the table test, but not as well as their task performance would predict.

Method

Participants. Eighty undergraduate students enrolled in introductory psychology courses at Louisiana State University were recruited to voluntarily participate in return for extra credit. These participants were randomly assigned to either the short (N = 40) or long (N = 40) training condition.

Task. The reactor control task, used in both experiments, is a computer-based task in which participants imagine they are the manager of a nuclear reactor (see figure 1). Participants attempted to achieve and maintain a specified level of an output variable, reactor temperature, by controlling the number of fuel pellets consumed by the reactor. Participants were given the goal of maintaining temperature at 6000 degrees. Task trials were grouped into blocks of six trials and each block began with a randomly selected reactor temperature level. On each task trial, participants saw a display which depicted two graphs; output temperature and number of fuel pellets input. On both graphs, trial number was depicted on the X-axis, while output temperature or number of fuel pellets entered was depicted on the Y-axis. Reactor temperature varied from 1000 degrees to 12000 degrees in 1000-degree increments. A horizontal line was positioned

across the entire output graph at the 6000 degree level to remind participants of the goal state. Participants selected a number of fuel pellets ranging from 100 to 1200 in multiples of 100. Participants responded by entering the number of pellets to be fed into the reactor. This was done by clicking on one of twelve input buttons on the left side of the screen. The computer then determined the new output level based on a formula and displayed the new output on the temperature graph. At the end of each block (every 6 trials), the display was cleared and a new graph was displayed for the next block of trials. The main dependent measure was the mean unsigned deviation from target production, in degrees. Response times were also recorded.

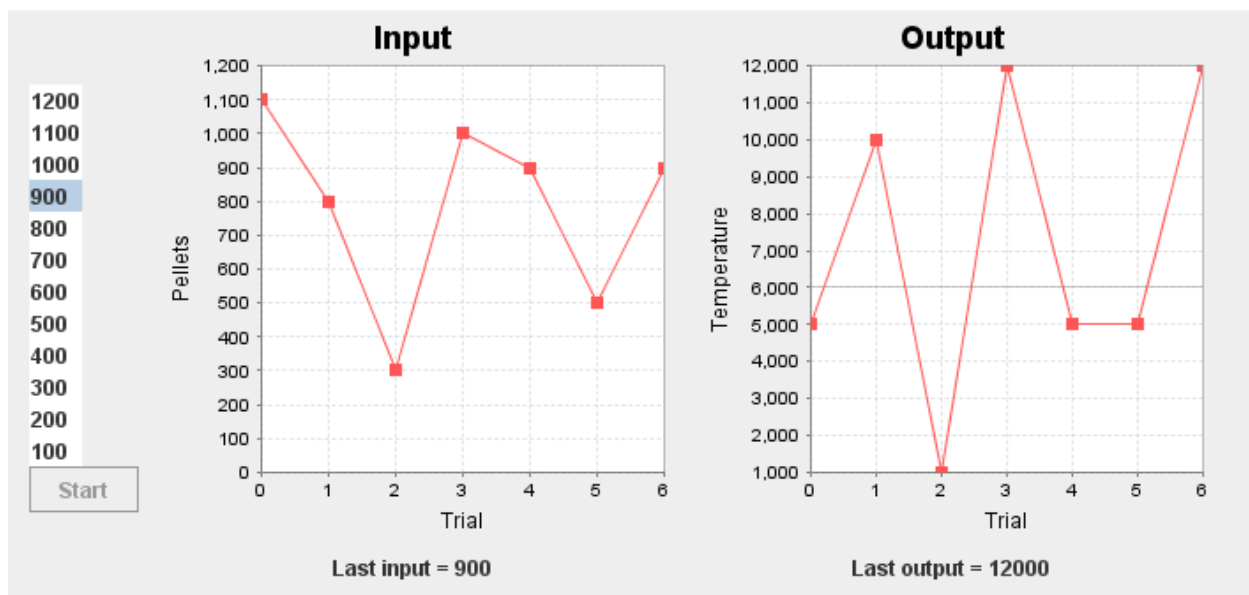


Figure 1. Reactor control task.

Procedure. Participants were tested in groups up to eight. Each group was randomly assigned to one of two conditions. Participants completed a prescribed number of practice trials followed by the extended range test, the new goal test, and the table test, in that order.

During the practice phase, participants were instructed to take on the role of manager of a nuclear reactor, where their job was to achieve and maintain a target temperature level (6000 degrees) by interacting with the simulator. They were told that the only variable they would control was the number of fuel pellets entered into the reactor, which would be done by clicking on the button with the corresponding number of fuel pellets with their mouse. Participants in the short training condition completed 14 blocks (84 trials) while those in the long training condition completed 280 blocks (1680) trials.

After completing the practice phase, participants completed the extended range test. This test required participants to enter an input for a given output. The interface for this test was the same as the practice trials, but this test was comprised of a series of single-trial blocks. An output between -3000 and 16000 was randomly selected and participants selected an input between 100 and 1200 fuel pellets. After selecting an input, participants choose between placing a large or small wager on the outcome of their response. No feedback was given in terms of the resulting output state nor the status of the wager. After the wager was selected, the computer redrew the screen with a new output level. This continued until participants responded to all outputs between -3000 and 16000. This test used a single trial format to limit the amount of exposure to the task for participants in the short training condition. Using a six-trial block like the practice phase would have more than doubled their exposure to the task and provided feedback during that exposure. The test ended after participants responded to all 20 output states.

After completing the extended range test, participants took the new goal test. This test consisted of 30 blocks and followed the procedure of the practice phase with the only change being that participants will be instructed to maintain an output of 8000 instead of 6000 degrees. Like the practice phase, a horizontal line was drawn across the output graph at the goal state of 8000 degrees.

Finally, participants completed a text-based table test which required them to provide the correct number of fuel pellets for each output state (from 1000-12000 in increments of 1000) to achieve a temperature of 6000 degrees (e.g. "If the temperature is 9000 how many fuel pellets should you enter to move the reactor's temperature to 6000").

Results

The primary variable of interest was performance, or unsigned deviation from the goal state, with a lower score indicating better performance. A log transformation, $\log_{10}(\text{deviation}+1)$, was performed on deviation scores due to the high variability of the scores. A constant of 1 was added to all deviation scores so a deviation of 0 could be transformed, as the log of 0 is undefined. While untransformed means are reported (see Table 2), all analysis on performance scores were performed on transformed data.

After practice, participants first took the extended range test. Deviation from the goal state was measured, which allowed for analysis of performance on old states and transfer to new, extended range states. Reaction time was also measured to determine if participants were using different strategies to respond on old versus new states. In addition, participants made a wager after selecting their response for each output. This was done as a measure of confidence in their response.

Participants next took the new goal test and deviation and reaction time was measured. This test measured participants' ability to transfer their knowledge acquired while practicing the task when the goal was 6000 to a new goal output state of 8000. Again, reaction time was collected as a way to gain insight to the strategies participants used to transfer their knowledge.

Finally, the table test as a way to assess participants' ability to use their acquired knowledge in a different context. Better than chance performance on this test would indicate access to experientially acquired knowledge, rather than the knowledge being completely implicit.

Table 2. Mean deviation scores for Experiment 1.

	Last 5 Practice Blocks	Extended range Test-Old States	Extended range Test-New States	new goal Test	Table test
Long Training	2889 (831)	3667 (1513)	6266 (1667)	2766 (980)	2788 (1112)
Short Training	3079 (593)	5079 (1212)	6856 (1092)	3584 (623)	3677 (771)

Note. Standard deviations presented in parentheses.

Extended Range Test. Performance was analyzed using a 2x2 mixed factorial ANOVA with training condition (short, long) as a between-subject factor and state type as a within-subject factor (old, new) (see Figure 2). This analysis revealed a main effect of state type with performance on old items being superior to performance on new states ($M = 4372.9, 6560.9; F(1, 78) = 43.1, p < .001 \eta_p^2 = .44$). A significant main effect of condition was also found, with participants in the long training condition producing lower deviation scores than those in the short training condition ($M = 4966.2, 5967.7; F(1, 78) = 5.89, p < .05 \eta_p^2 = .07$). The main effects were qualified by an interaction revealing that the superior performance of the long condition was only

observed on old states ($F(1, 78) = 4.2, p < .05, \eta_p^2 = .051$). Subsequent analysis revealed that performance of both groups was better than chance on old states but did not differ from chance on new states. Chance deviation from goal on old states was 5792 and 6473 on new states.

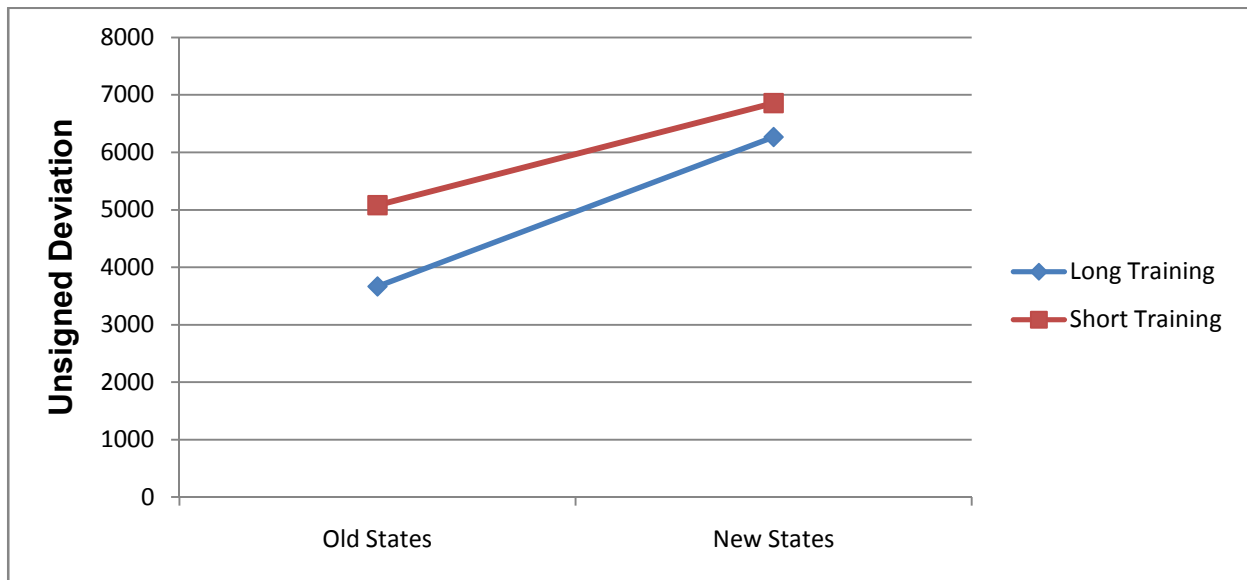


Figure 2. Performance on extended range test in Experiment 1. Dependent measure is the absolute deviation from target.

Due to the long practice phase, there were no old-incorrect states on the extended range test for participants in the long training condition, meaning there was at least one loosely correct response for each output state during practice. This was not the case for those in the short training condition. Analysis revealed that performance on old-correct states was superior to that on old-incorrect ($M = 4261.4, 5929.9; t(39) = 2.54, p < .05$). While performance on old-incorrect states was inferior to old-correct states, performance on old-incorrect states still significantly better than chance, unlike performance on new states.

Similar analyses were conducted on reaction time data from the Extended range test (see Figure 3). A main effect of group was found, with participants in the long

training condition responding more quickly than those in the short training condition ($M = 4563.4, 6475.5$; $F(1, 78) = 16.3, p < .001, \eta_p^2 = .172$). A main effect of state type was found as well, with participants responding more quickly on new states than old ($M = 4933.8, 6105.1$; $F(1, 78) = 12.6, p < .01, \eta_p^2 = .139$). There was no significant interaction ($F < 1$). Additionally, no difference was found in reaction times between old-correct and old-incorrect states for participants in the short training condition.

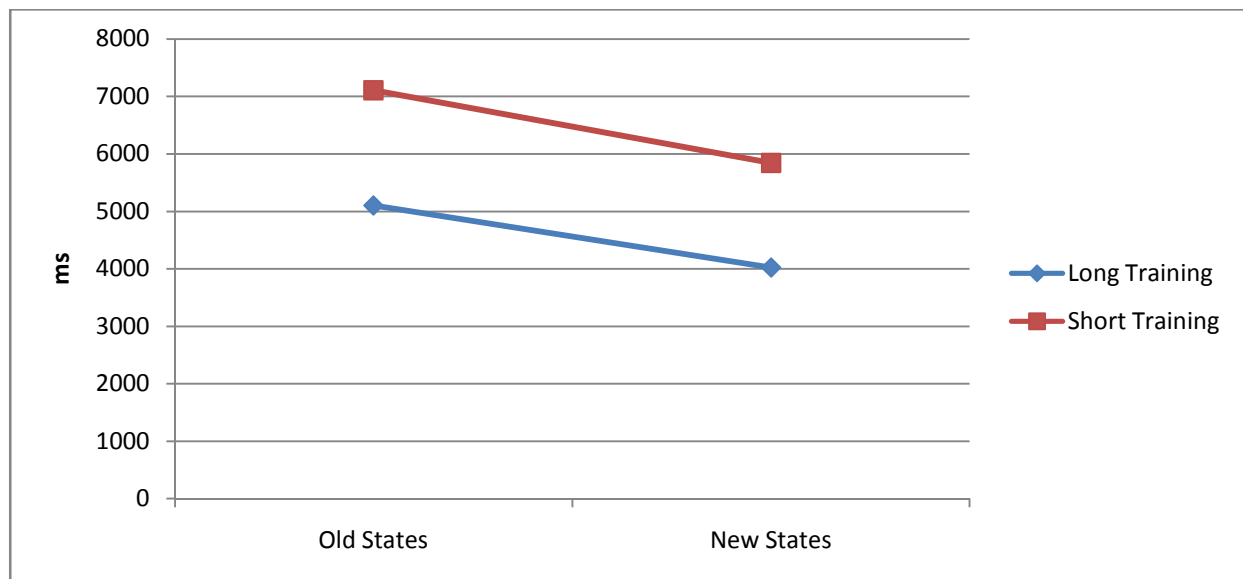


Figure 3. Reaction time on extended range test in Experiment 1. Dependent measure is the reaction time in ms.

Taken together, data from the extended range test suggest a lookup table model at both levels of training as predicted by Dienes and Fahey (1995, 1997). Both a general rule model (Lane et al., 2007) and a strategy tuning model (Fum & Stocco 2003a, 2003b) would predict similar performance across both old and new states, while a lookup table model would predict better performance on old states. While chance performance and fast responses on new states is consistent with Cleeremans' model, (described in Marescaux, Luc & Karnas, 1989) which predicts that situations for which

there is no stored output-input pair are answered with a random input, a visual analysis of the distribution of inputs for new states suggests participants were responding incorrectly, but not randomly. Participants in the short training condition tended to input low levels of fuel pellets across all new states. This pattern is difficult to interpret. If participants were using some strategy based on real world knowledge (e.g. if the temperature is very high, enter a low level of fuel pellets), one would expect low levels of pellets inputted at high temperature levels and high levels of pellets at low temperatures. Instead, low levels of pellets are input across all new states. Again, this pattern is difficult to interpret but it is not random. While this is inconsistent with Cleereman's model, it is important to note that new states in that model were states within the standard range (1000-12000) which were not encountered during a very short practice phase.

Participants in the long training condition demonstrated a more easily interoperated strategy. Here, participants tended to avoid entered very low (100, 200) or very high (1100, 1200) levels of fuel pellets. While this strategy lead to poor performance on the extended range states, it is a valid strategy for responding to old states. Participants learned through practice that very high and low inputs always led to extreme outputs (1000, 12000) and seemed to use this strategy at new states which lead to poor performance. Because no feedback was given on the extended range test, there was no opportunity for participants to see that this strategy did not work. This pattern of results in both the short and long training conditions is consistent with Dienes and Fahey's (1995) model suggesting that responses to new states are generated using a strategy.

In addition to deviation and reaction time measures, a knowledge score was derived from participants wagering behavior. The knowledge score was the proportion of correct wagers; high wager when correct or low wager when incorrect. An analysis revealed a significantly higher knowledge score for participants in the long training condition ($M = .664, .573$; $F(1, 78) = 4.56, p < .05 \eta_p^2 = .055$). Additional analysis revealed the knowledge scores of both groups to be significantly above chance (.5). A knowledge score above chance in both conditions would suggest that participants have some access to the knowledge used to perform the task, contrary to notion that experientially acquired knowledge is implicit, or inaccessible.

New Goal Test. The effect of training condition on transfer to a new goal was analyzed using a 2 x 2 mixed factorial ANOVA with training condition (short, long) as a between-participants factor and goal as a within-participants factor (6000, 8000) (see Figure 3)¹. The analysis revealed a main effect of condition, with participants in the long training condition performing better than those in the short training condition ($M = 2766, 3584$; $F(1, 78) = 4.0, p < .05 \eta_p^2 = .048$). A main effect of goal was also found with superior performance seen at the goal of 6000 ($M = 2834, 3175$; $F(1, 78) = 8.76, p < .005 \eta_p^2 = .101$). A trend towards an interaction was also found ($F(1, 78) = 3.83, p = .054 \eta_p^2 = .047$). A planned comparison paired-sample t-test revealed a significant decline in performance in the short training condition ($t(39) = -3.35, p < .01$). No significant difference was found between goals in the long training condition ($t < 1$). Both groups performed better than chance on the new goal test.

¹ Performance at the 6000 goal was derived from the participants' mean deviation from 6000 over the last five blocks during the practice session. Performance on the extended range test was not used because it does not allow for multiple step procedures. Some participants may have developed a strategy in which they use two or more steps to reach the target (e.g. enter 1200 to move to the top of the range, and then enter 900) which would not have been captured on their performance on the Extended range test.

A similar analysis on reaction time data showed a significant main effect of condition (see Figure 5), with participants in the long training condition responding more quickly than those in the short training condition ($M = 1091, 2918$; $F(1, 78) = 25.5, p < .001, \eta_p^2 = .247$). A main effect of goal was also found, showing faster reaction times at the goal of 6000 ($M = 1535.9, 2004.3$; $F(1, 78) = 25.8, p < .001, \eta_p^2 = .249$). There was no significant interaction ($F < 1$).

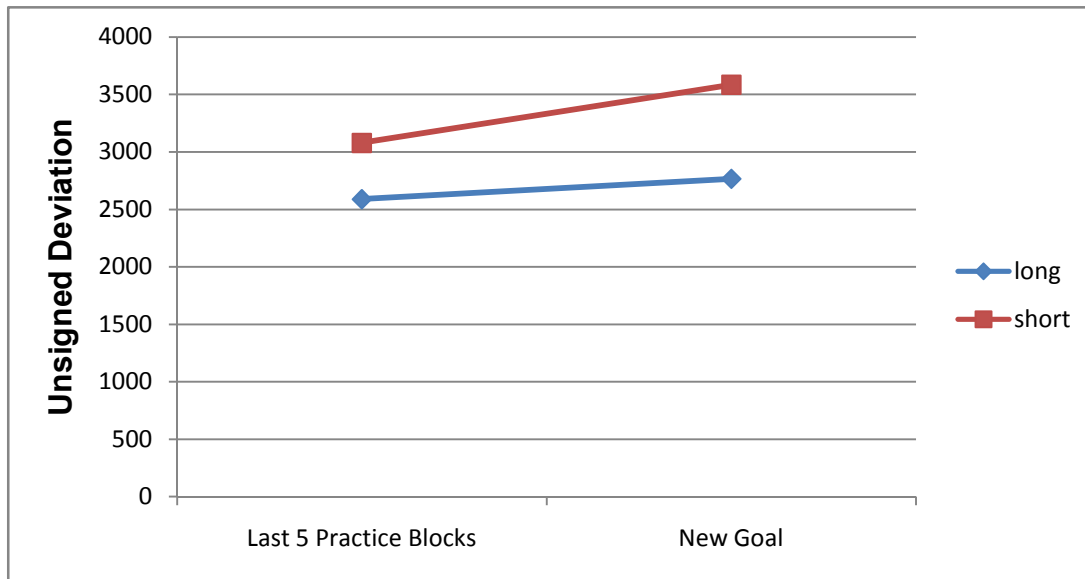


Figure 4. Performance on the last 5 blocks of practice and the new goal test in Experiment 1. Dependent measure is the absolute deviation from target.

Like the extended range test, these data are consistent with a lookup table model (Dienes & Fahey 1995, 1997). A general rules model (Lane et al., 2007) and a strategy tuning model (Fum & Stocco 2003a, 2003b) would predict similar performance across both goals. While participants in the long training condition did not exhibit a significant decline in performance on the new goal test, they, along with the short training condition, did show significantly slower reaction times. This is consistent with the use of an extrapolation procedure to derive new actions based on old condition-action (output-

input) pairs. A general rule or set of tuned strategies would not predict slower reaction times.

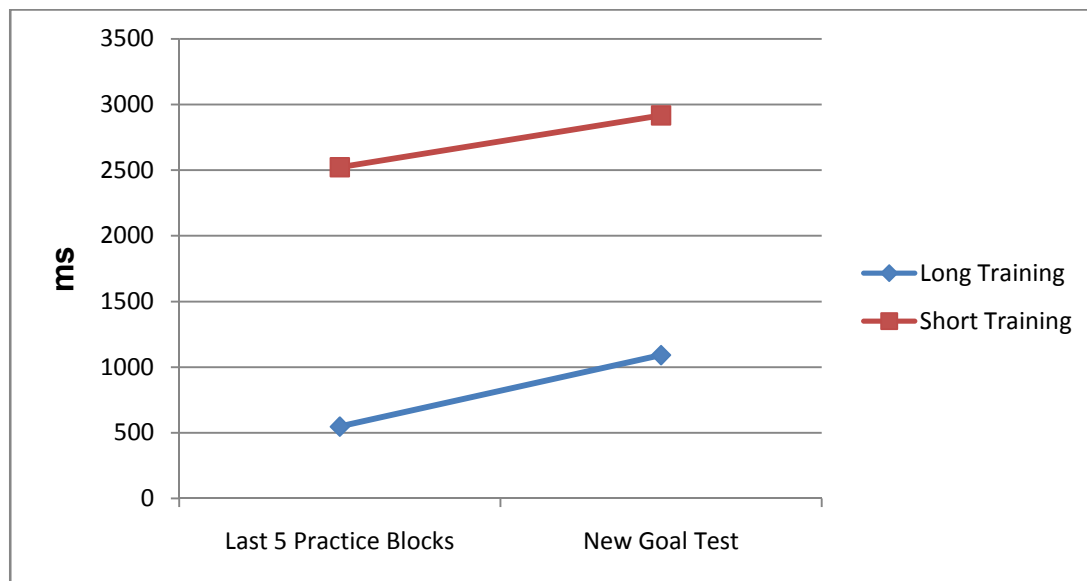


Figure 5. Reaction time on last 5 blocks of practice and new goal test in Experiment 1. Dependent measure is the reaction time in ms.

Table Test. A one-way ANOVA with group as the between subjects factor revealed a significant difference in table test performance between the long and short training conditions ($M = 2788, 3677$; $F(1, 78) = 10.9, p < .01, \eta_p^2 = .123$). Performance of both groups is better than chance (see Figure 6). An analysis of the correlation between performance on the last 5 blocks of practice and performance on the table test showed a significant positive correlation for the long training condition ($r = .373, p < .05$) and no significant correlation in the short training condition ($r = .144, ns$). Like the data from the wagering task, these data run contrary to the idea that participants do not have access to any knowledge of the task. Better than chance performance demonstrates that participants in both conditions can use knowledge learned in one setting (a dynamic task with graphic displays) to a static task with questions asked in text form. Along the same line, superior performance in the long training condition demonstrates greater

access to task knowledge as practice increases. Also, the significant correlation in the long but not short training condition suggests as task knowledge increases, so does access to that knowledge. This is in line with Stanley, et al. (1989) who argued that access to task knowledge increases with practice but lags behind task performance.

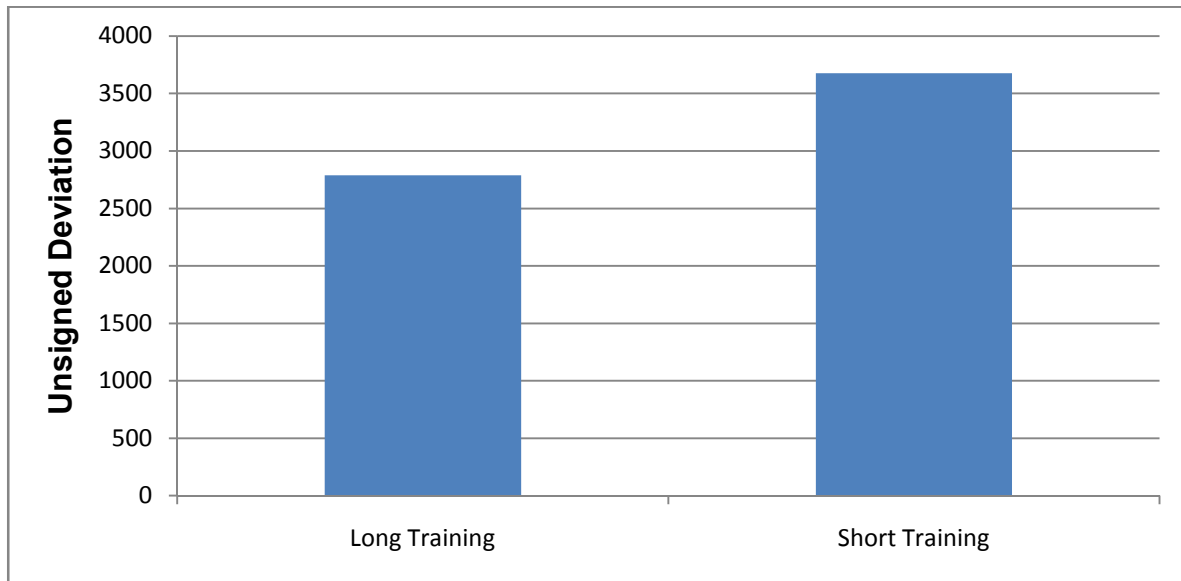


Figure 6. Performance on the table test in Experiment 1. Dependent measure is the absolute deviation from target.

Discussion

The results of Experiment 1 replicated Lane et al. (2007) by demonstrating transfer to a new goal with experiential practice. However, transfer to new states was not observed. To return to the original hypotheses, the results of Experiment 1 suggest that knowledge of the process control task is represented as a lookup table, rather than a set of tuned strategies (Fum & Stocco, 2003a, 2003b). The data fit well with a lookup table comprised of specific output-input pairs (Dienes & Fahey, 1995, 1997).

Participants were able to transfer to a new goal, but with a significant cost in response time which may indicate the use of an extrapolation procedure. This transfer could also be explained by a more general, contextualized table comprised of general rules (Lane

et al.) where an effective rule for a goal of 6000 (if temperature is high, input 800 fuel pellets) may be slightly less effective when the goal changes to 8000. Unlike transfer to a new goal, participants were not able to transfer to new states. While on the surface, this pattern seems to be consistent with Cleermans' argument (described in Marescaux, Luc & Karnas, 1989) that unseen states are answered randomly, further inspection revealed strategic, but incorrect responses.

In addition to addressing the issue of flexibility, awareness of experientially acquired knowledge was also assessed. The results of the wagering task and the Table test demonstrate that even with very little practice, participants have some awareness of the knowledge used to operate the process control task and that awareness increases with practice. This is contrary to the idea of an implicit lookup table proposed by Dienes and Fahey (1995, 1997)

While this representation does not seem to change as amount of practice is increased, it is important to note that participants in the long practice condition in Experiment 1 completed only one-third of the training trials as those in Lane et al. Future research should investigate if extremely high levels of practice result in a shift in knowledge representation from a lookup table to a general rule.

EXPERIMENT 2

The goal of Experiment 1 was to investigate the flexibility of knowledge acquired through experiential practice with the process control task. Results revealed that regardless of practice level, task knowledge was represented as a specific lookup table. While in the laboratory, it is appropriate to study experiential practice in isolation, but real world learning often combines experiential practice and model-based knowledge. Experiment 2 sought to examine the flexibility of knowledge as a function of instruction type.

Instruction, at a simple level, can be divided into two types. In direct instruction, complete knowledge is provided directly by the teacher to the learner (Kirschner, Sweller, & Clark, 2006). In experiential practice, the learner is given very little guidance and is said to construct the knowledge themselves (Bruner, 1961; Papert, 1980, Steffee & Gale, 1995). While the experiential practice method is very popular with educators, its efficacy has been questioned (Klahr & Nigam 2004; Mayer, 2004). Proponents of experiential practice argue that excessive guidance during acquisition may impair the learner's performance on tests of retention and transfer (Kirschner, Sweller, & Clark, 2006) However, in a review of the literature, Mayer (2006) consistently found superior task performance learners taught using direct instruction and no advantage of experiential practice on tests of retention or transfer performance.

While the Mayer's (2004) work would make it seem that direct instruction is the superior pedagogical methodology, the results of Lane et al. (2007) cast some doubt onto this argument. Lane, et al. found that providing participants with a complete lookup table before practice with the task produced superior performance on the process

control task when compared to participants who practiced the task without a table. There were, however, costs associated with this provided lookup table. Specifically, a significant decline in performance was observed when time to respond was limited (speeded test) or when the goal state was changed (new goal test). Although performance declined when the task parameters of the task changed, transfer performance in this table group was at similar levels to those subjects in the practice-only condition. Lane, et al., suggested that some experiential knowledge, gained through practice with the task, was acquired in addition to the lookup table. However, as detailed in the introduction, it is unclear whether participants in Lane, et al. who memorized the table before experiential practice acquired as much experiential knowledge as participants who practiced the task without a table. When using very precise model-based knowledge, learners may get limited exposure to the task. By only entering the correct input for a given output, learners do not explore the problem space, thus reducing the amount of experientially acquired knowledge. While direct instruction improved task performance, providing that instruction before experiential practice may not be the optimal point for its introduction. Thus it is possible that proponents of both direct instruction and experiential practice are partially correct, and that the best pedagogical approach is a combination of the two.

To examine this issue, Experiment 2 used the same Nuclear Reactor task as Experiment 1. Participants engaged in a practice phase followed by a standard test, in which the goal was 6000 degrees, a speeded test where time to respond was limited to 1100 ms, an extended range test with wagering, a new goal test, and table test. Participants were assigned to 1 of 7 conditions; four training conditions and three no-

training control conditions. The amount of training was consistent across the training conditions, but the point at which a lookup table was provided differed. Participants in the pre-training condition memorized the table before practice began, those in the in-training condition were given the table after completing half of the training trials, and those in the post-training condition received the table after training was completed. A no-table training condition completed the full practice phase, but did not memorize the lookup table. In addition, four control conditions were run. The standard test control took the standard test with no prior experience. The standard test table-control memorized a lookup table calibrated for the goal output of 6000 and took only the standard test. The new goal control condition took only the new goal test.

This procedure allowed for testing several hypotheses. The first hypothesis is that the point of introduction of model-based knowledge will affect the amount of experiential knowledge acquired. Lane, et al. (2007) demonstrated the facilitative effects of providing model based knowledge on task performance. Experiential practice before model-based knowledge may increase the amount of experiential knowledge acquired, thus combining the precision of model-based knowledge and the flexibility of experiential knowledge. If providing model based knowledge limits participants' exploration of the problem space, participants may not experience a wide enough range of instances which may limit the amount of experiential knowledge acquired. If this is the case, participants who memorize the table before practice should perform as well as participants who memorize the table during and after practice on the Standard test, but may show worse performance than those two conditions when the goal is changed and on "new" states in the extended range test. This pattern of results would suggest that

providing model-based knowledge before practice limits the amount of experiential knowledge participants acquired. However, it is also possible that providing model-based knowledge after practice may be sub-optimal. In this case, participants may not have an opportunity to integrate the lookup table with their experiential knowledge, or memorizing the lookup table may interfere with the deployment of experiential knowledge.

Providing model-based knowledge before practice may limit the acquisition of experiential knowledge while providing it after practice may interfere with the deployment of experiential knowledge. It is possible that providing model-based knowledge half-way through practice will allow participants to both acquire experiential knowledge and then integrate the provided model-based knowledge into their representation of the task. If this prediction is correct, the data will show superior performance in participants who memorize the table during training across the standard, new goal, speeded, and extended range tests compared to participants in the pre-training and post-training conditions.

Method

Participants. A total of 265 undergraduate students enrolled in introductory psychology courses at Louisiana State University were recruited to voluntarily participate in return for extra credit. These participants were randomly assigned to one of seven conditions. There were four training conditions: Pre-Training (N = 37), In-Training (N = 40), Post-Training (N = 37), and No-Table Training (N = 37). In addition, there were also three control groups: standard test Control (N = 37), standard test Table-Control (N = 38), new goal Control (N = 39).

Task. The same reactor control task used in Experiment 1 was used in Experiment 2.

Procedure. Participants were tested in groups up to eight. Participants in the training conditions completed 280 blocks of six trials in which the goal was to maintain a goal output of 6000 degrees. Participants in the Pre-Training condition memorized a full lookup table before training, those in the In-Training condition memorized the lookup table after completing 140 blocks, and those in the Post-Training condition memorized the table after completing all 280 blocks. Participants in all table conditions were given a set of 12 index cards, with an output level on one side of the card, and the correct input on the reverse. Participants were instructed to learn the correct input for each output level and told that they would complete a quiz before being allowed to proceed. After reviewing the cards, participants were given a fill-in-the-blank paper quiz with 12 questions, one for each output level (i.e. If the temperature is 1000 degrees, how many fuel pellets should you input?). Participants in the No-Table Training condition completed 280 trials but did not memorize the table.

After completing the training phase, participants took a 30-block standard test. This test is similar to the training task in that participants were required to maintain a goal output of 6000 degrees. Participants then took a 30-block speeded test in which the goal is 6000 and response time was limited to 1100 ms. This response time was chosen based on a pilot test which included the author who has extensive experience with the task. During pilot testing, the response time was increasingly lowered until testers found it difficult to maintain the target output. If participants did not respond within the time limit, the computer entered a random input. Following the speeded test,

participants took the extended range test. Like in Experiment 1, the output range was extended from -3000 to 16000 degrees and participants placed a wager before receiving feedback. The extended range test was followed by a 30-block new goal test where the goal was 8000 degrees. Finally, participants complete a table test similar to that in Experiment 1.

Participants in the standard test control took only the standard test with no prior experience with the task. Those in the standard test table-control memorized the table before taking the standard test. Participants in the new goal control took the new goal test with no prior experience with the task.

Results

After practice, participants first the standard test with the goal state set at 6000, the same as in practice. The analysis run on the data from this test compared performance of participants who learned the table and practiced, participants who only practiced, participants who learned the table but did not practice, and participants who did not learn the table or practice the task. The purpose of this analysis was to demonstrate that practice alone is better than no practice, but that table knowledge alone is comparable to table knowledge and practice on the standard test.

The next analysis reported is the from the new goal test. Like in Experiment 1, the new goal test measured participants' ability to transfer their knowledge from the goal of 6000 to 8000. In addition to comparing performance across goals, a difference score was calculated by subtracting performance on the standard test from that on the new goal test. This allowed for a comparison of the decline in performance between learning conditions to see which groups were most hindered by the change in goal.

A similar analysis to that conducted on the new goal data was conducted on data from the speeded test. This test allowed for a comparison of performance on the standard test, and performance when time to respond is limited. A difference score was calculated to compare the decline in performance across conditions.

As in Experiment 1 performance on the extended range test was compared across old and new states as a measure of transfer. A knowledge score was also calculated for each participant by dividing the number of advantageous wagers by the total number of wagers.

Performance on the table test was measured in mean deviation from target. This test was a measure of how well knowledge acquired in the graphical setting could be applied to the same task in a text format. This along with the knowledge score was a measure of how accessible task knowledge was.

Standard Test. As in Experiment 1, untransformed means for deviation are reported (see Table 3) while analyses were performed on transformed data. A 2 x 2 ANOVA with exposure to practice (practice, no practice) and exposure to the lookup table (lookup table, no lookup table) as factors was conducted (participants who learned the table before, during, and after practice were collapsed into one group for this analysis). There was a main effect of exposure to practice in which participants who practiced the task before the standard test exhibited superior performance to those who did not practice ($M = 1882, 2249$; $F(1, 222) = 7.87, p < .05, \eta_p^2 = .034$). There was also a main effect of the lookup table, such that participants who memorized the table showed superior performance compared to those who did not memorize the table ($M = 1154, 2934$; $F(1, 222) = 281.8, p < .001, \eta_p^2 = .559$). There was also an interaction (F

(1, 222) = 4.5, $p < .05$ $\eta_p^2 = .02$). A follow up one-way ANOVA revealed that participants who memorized the table and practiced ($M = 1112$) showed no significant performance advantage over those who only memorized the table ($M = 1280$). Both of those conditions displayed superior performance to that of participants who practiced but did not memorize the lookup table ($M = 2651$), and all conditions were superior to participants who did not practice or memorize the lookup table. These results show no performance advantage of practice when participants have access to the lookup table. However, when no lookup table is available, participants who practice show superior performance to those who do not practice. This demonstrates that memorizing a lookup table results in the best performance, but some knowledge is gained though experiential practice as well.

Table 3. Mean deviation scores from Experiment 2.

	Standard Test	Extended Range Test-Old States	Extended Range Test-New States	Speeded Test	New Goal Test
Pre-Training	941 (237)	1210 (840)	2578 (1973)	2485 (748)	2018 (518)
In-Training	1186 (697)	1285 (1161)	2594 (2665)	2461 (569)	1696 (793)
Post-Training	1205 (665)	1552 (1206)	2517 (2018)	2876 (533)	1833 (942)
No-Table Training	2651 (696)	3917 (1679)	6422 (1565)	2870 (259)	2951 (862)
standard test Control	3218 (502)	-	-	-	-
standard test Table-Control	1280 (793)	-	-	-	-
new goal Control	-	-	-	-	3681 (469)

Note. Standard deviations presented in parentheses.

New Goal Test. A one-way ANOVA (including new goal control) analyzing deviation scores on the new goal test was significant by group ($F(3, 183) = 28.4, p < .001, \eta_p^2 = .383$). A Dunnett's t-test compared all groups against the control and found a significant performance advantage for all groups relative to the control. This analysis demonstrates that even with training alone, participants can transfer knowledge to a new goal.

A 4 x 2 ANOVA with condition (Pre-Training, In-Training, Post-Training, and No-Table Training) as a between-subject factor and test as a within-subject factor (Standard test, new goal Test) was also run (see Figure 7). A main effect of condition was found, with conditions that memorized the table performing better than those who did not ($F(3, 147) = 29.5, p < .001, \eta_p^2 = .376$). A main effect of test type was also found, as participants performed better on the standard test compared to the new goal Test ($M = 1489, 2018; F(1, 147) = 135.7, p < .001, \eta_p^2 = .48$). An interaction was also found ($F(3, 147) = 20.0, p < .001, \eta_p^2 = .29$). A one-way ANOVA run on the difference scores between new goal and standard test performance revealed that some groups declined more than others ($F(3, 147) = 19.9, p < .001, \eta_p^2 = .29$). While all conditions performed poorly on the new goal test relative to the standard test, the No-Table Training condition showed the smallest decline. Both the In-Training and Post-Training conditions exhibited a larger decline across tests than the No-Table Training condition, and the Pre-Training condition showed the largest decline of all (see Figure 8). A follow up one-way ANOVA on the new goal test found a main effect of condition ($F(3, 147) = 11.8, p < .001, \eta_p^2 = .191$). A Tukey post hoc test showed that participants in the Pre-Training condition exhibited worse performance at the new goal than those in the In-

and Post-Training conditions. This suggests that the Pre-Training condition acquires less knowledge which can be transferred than other conditions. One possible explanation for this is that when participants have the lookup table before practice began, they know the correct input for each output and spend little time exploring the problem space. An analysis of the number of trials at each output state revealed that participants in the Pre-Training condition spent 67% of trials in the practice phase at 5000, 6000, and 7000, significantly more than any other condition.

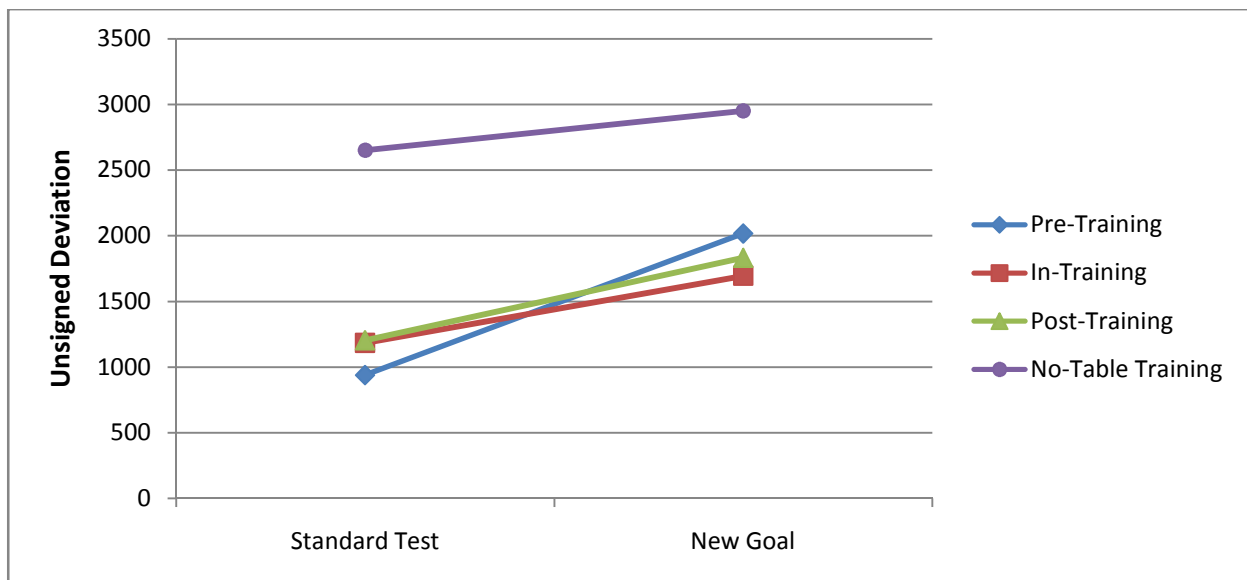


Figure 7. Performance on the standard test and the new goal test in Experiment 2. Dependent measure is the absolute deviation from target.

Better performance on the new goal test by participants who memorized the lookup table suggests that the lookup table along with some correction factor is used when the goal changes. While those who do not memorize the lookup table show a small decline when the goal is changed, their performance is still far worse than those in the lookup table conditions. Thus, experiential knowledge is transferable across goals, but experiential knowledge and a well-defined lookup table results in superior transfer

performance. Clearly, providing the lookup table prior to a transfer test is necessary for good transfer performance.

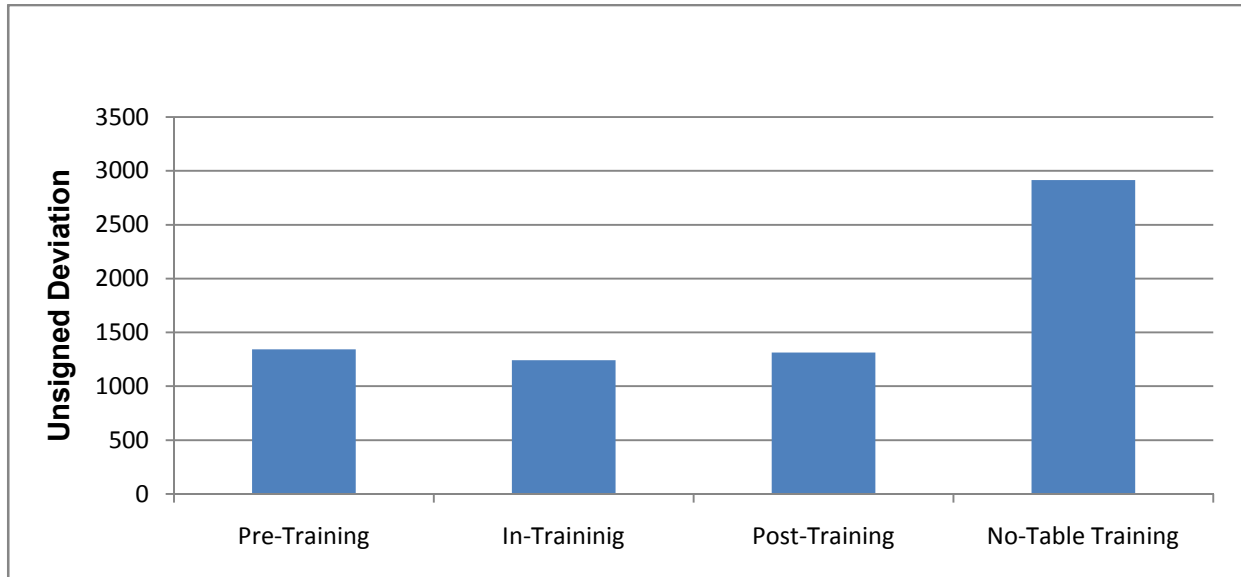


Figure 8. Difference score between standard test and new goal test. Dependent measure is the absolute deviation from target.

One important factor when providing model-based knowledge seems to be the point at which it is introduced, as those who practiced the task before memorizing the table showed a smaller decline across tests. It may be that experience with the task before the introduction of model based knowledge allows greater exploration of the problem space, which in turn results in the acquisition of more experiential knowledge. Participants who memorized the table prior to practice were focused only on recalling the correct input for each output and did not acquire the experiential knowledge necessary for transfer to a new goal.

Speeded Test. Another 4 x 2 ANOVA with condition (Pre-Training, In-Training, Post-Training, and No-Table Training) as a between-subject factor and test as a within-subject factor (standard test, speeded test) was run (see Figure 9). A main effect of

condition was found ($F(3, 147) = 34.6, p < .001 \eta_p^2 = .414$) in which participants who did not memorize the lookup table showed worse performance than those who did. There was also a main effect of test type with performance on the standard test superior to that on the speeded test ($M = 1489, 2669; F(1, 147) = 349.6, p < .001 \eta_p^2 = .704$). A significant interaction was found ($F(3, 147) = 27.1, p < .001 \eta_p^2 = .356$). An analysis of difference scores between the two tests show that all conditions but the No-Table Training condition exhibited a significant decline in performance on the speeded test. Additional post hoc analyses found no significant difference between the Post-Training and No-Table Training conditions on the speeded test, suggesting that participants in the Post-Training fell back on experiential knowledge rather than using the lookup table when time to respond was limited (see Figure 10). This is in line with Anderson's (1983) idea that with extensive practice, declarative knowledge (lookup table), which is slow to deploy, becomes proceduralized, or automatic. Those participants in the Post-Training condition did not have extensive practice deploying the lookup table, and therefore were unable to use it when time was limited.

Extended Range Test. Performance on the extended range test was analyzed using a 2 x 2 mixed factorial ANOVA with training condition as the between-subject factor and state type (old states, new states) as the within-subject factor (see figure 11). A main effect of condition was found ($F(3, 147) = 43.3, p < .001 \eta_p^2 = .469$) in which the No-Table training condition performed worse than all other conditions. There was also a main effect of state type, with a smaller deviation from goal on old states compared to new states ($M = 1977, 3509; F(1, 147) = 53.0, p < .001 \eta_p^2 = .265$). An interaction was also found ($F(3, 147) = 6.6, p < .001 \eta_p^2 = .119$). A follow up analysis using paired

sample t-tests showed that all groups decline in performance from old states to new. However, a one-way ANOVA on the difference between old and new states showed that the decline in performance of No-Table Training condition was greater than that of all other conditions. Furthermore, performance in this condition was at chance on new states, suggesting random responding as in Experiment 1.

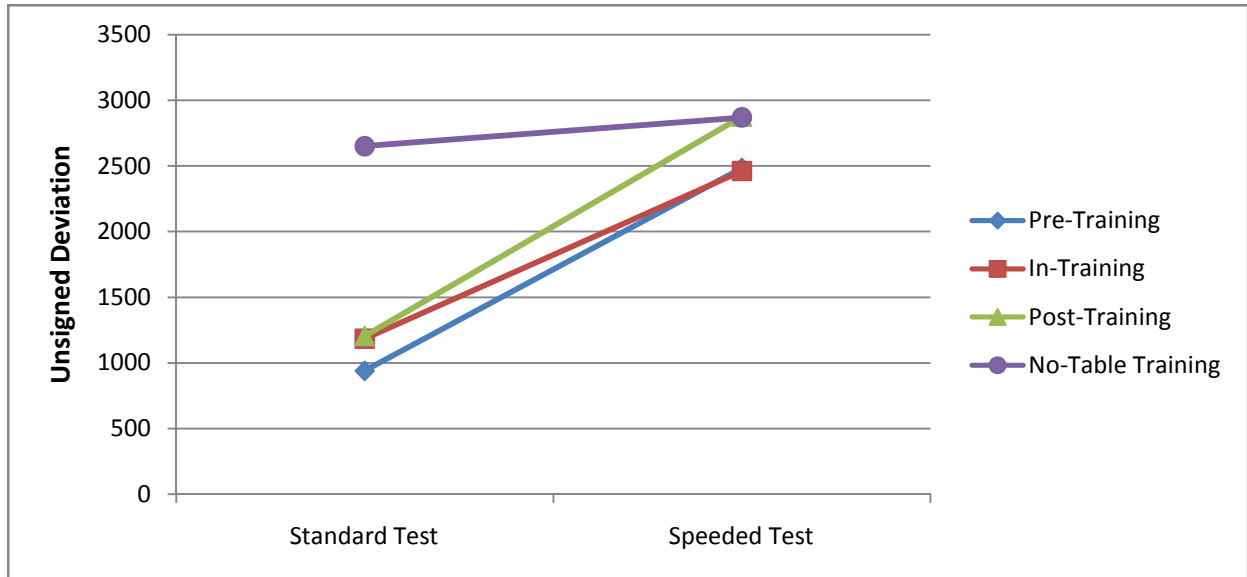


Figure 9. Performance on standard test and the speeded test in Experiment 2. Dependent measure is the absolute deviation from target.

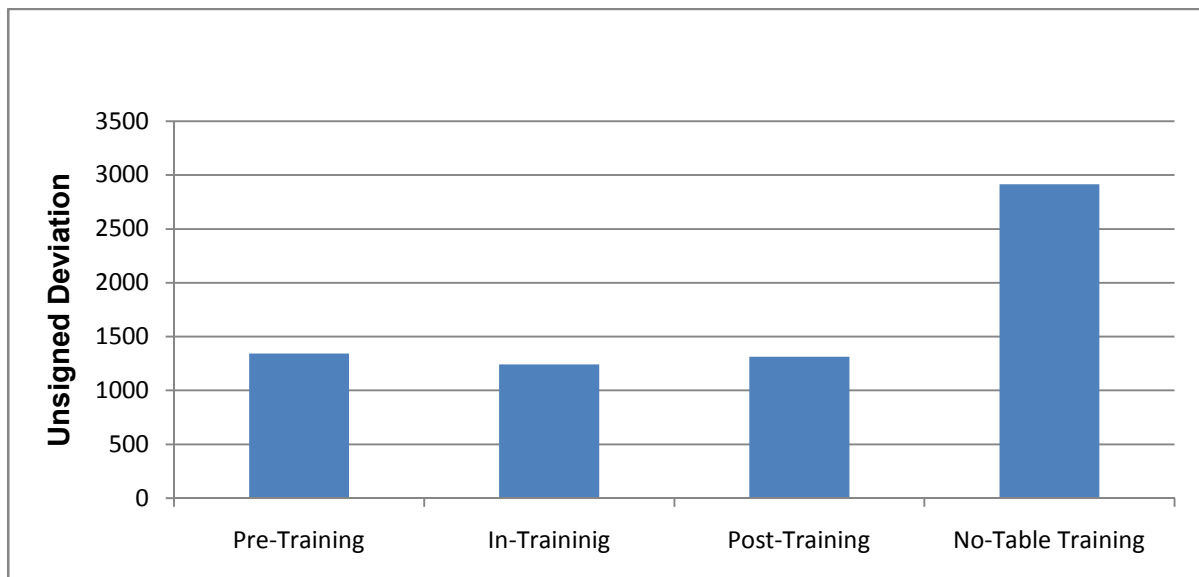


Figure 10. Difference score between standard test and speeded test. Dependent measure is the absolute deviation from target.

The same 2 x 2 ANOVA was run on data from the wagers made during the Extended range Test. A main effect of condition was found ($F(3, 147) = 40.4, p < .001, \eta_p^2 = .452$) with No-Table Training winning significantly less than other conditions. An effect of state type was also found with participants winning more money on old states than new ($M = 55.2, -3.7; F(1, 147) = 353.1, p < .001, \eta_p^2 = .706$). An interaction was also observed ($F(3, 147) = 16.6, p < .001, \eta_p^2 = .253$) such that the No-Table training condition shows a smaller decline (greater losses) in winnings from old to new states than all other conditions.

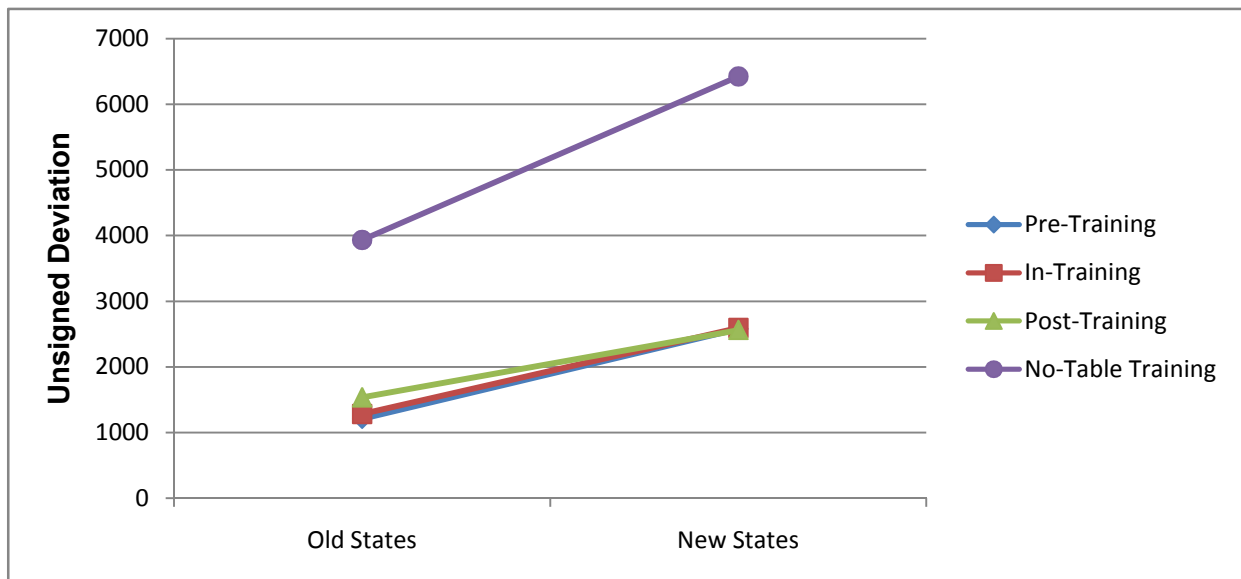


Figure 11. Performance on old and new states from the extended range test in Experiment 2. Dependent measure is the absolute deviation from target.

Like in Experiment 1, a knowledge score was calculated by dividing the number of advantageous wagers (high when correct, low when incorrect) by the total number of wagers. No significant differences between conditions were observed ($F(3, 147) = .32, ns$) and all conditions were above chance. There was a difference in total amount wagered ($F(3, 147) = 8.4, p < .001, \eta_p^2 = .147$) such that the No-Table Training condition

wagered less than all other conditions. When broken down between old and new states, participants who memorized the table wagered more on old items than those in the No-Table Training condition. On new states, there was no difference in amount wagered. That the knowledge score data were above chance suggests that all participants had some knowledge of how they were performing the task. While those participants who memorized the table performed relatively well on new states, they did not consistently place high wagers at those states. This switch from high wagers on old states to low wagers on new states suggests that participants were not aware of how they were performing the task at new states. It is possible that they simply recalled an input for each old states, and used an extrapolation procedure for new states. This extrapolation hypothesis is supported by reaction time data which show that participants who memorize the table respond slower on new states. Recalling the correct input at an old state is fast, while extrapolating the lookup table to account for a new state is slow, and less accurate.

The results from Experiment 1 suggest that knowledge acquired from experiential practice takes the form of a lookup table. Thus, it is interesting that participants who memorize a lookup table can transfer their knowledge to new states, while those who presumably develop their own lookup table cannot. One possible explanation for this discrepancy is how the lookup table is organized. A self-generated lookup table may be poorly organized with multiple inputs for each output. Providing participants with one correct input for each output may have allowed them to see the “big picture”, or pattern across the output-input pairs, making transfer to new states more likely. Participants who developed their own lookup table through practice may not have organized their

table in such a way that would have allowed them to see the pattern. Without understanding the pattern, these participants were not able to extrapolate their table to new states and instead respond randomly, as evidenced by their chance level performance and significantly faster responses on new states.

Table Test. Performance on the table test was analyzed using a one-way ANOVA, and an effect of condition was found ($F(3, 147) = 11.7, p < .001, \eta_p^2 = .192$). A Tukey post hoc test revealed no significant difference between conditions which learned the lookup table, and significantly worse performance for the no-table training condition relative to the other three conditions (see Figure 12). This analysis demonstrates that while participants who learn the task through experiential practice have some access to the knowledge they use to operate in the task, their access is limited compared to those who learn the lookup table.

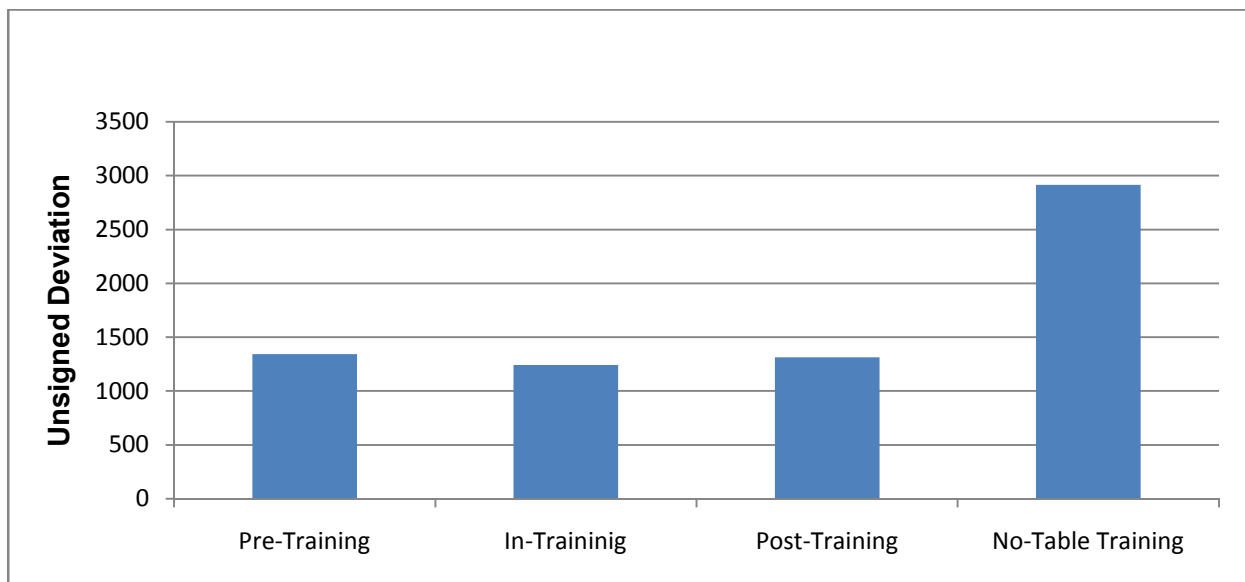


Figure 12. Performance on the table test in Experiment 2. Dependent measure is the absolute deviation from target.

Discussion

As expected, instruction type had an effect on flexibility of knowledge acquired. Of course, providing a lookup table improved performance on the standard test, but also on all other tests as well. The data from Experiment 2 suggest that participants who memorized a lookup table gained experiential knowledge from practicing the task. This resulted in significantly better transfer to a new goal than practice alone. Similarly, only participants who memorized the lookup table were able to transfer to new states. The level of experiential knowledge acquired seemed to have been affected by the point at which the model-based knowledge was introduced. Providing the lookup table prior to practice seemed to discourage exploration of the problem space, potentially limiting the amount of experiential knowledge acquired, and impeding transfer to a new goal. In addition, providing the lookup table after practice was also not optimal as experience with the table is needed before it can be quickly deployed, as in the speeded test.

GENERAL DISCUSSION

Experiment 1 examined the representation of experientially acquired knowledge as a function of practice duration. On the Extended range test, both the long and short training conditions exhibited better performance on old compared to new states. Performance on new states was at chance and responses on new states were significantly faster than old states. Taken together, these data suggest that participants were recalling the correct input for a given output on old states, and selecting a random input at new states. A strategy tuning model (Fum & Stocco 2003a, 2003b) would predict similar performance across old and new states as a strategy which worked for old states would be equally successful at new states. The data are more in line with a lookup table model such as that proposed by Dienes and Fahey (1995, 1998), although the chance performance on new states supports Cleermans' (see Marescaux, Luc & Karnas, 1989) idea that inputs at states not yet seen are chosen at random, not by some explicit strategy. These results do not rule a more general lookup table model (Lane et al., 2007).

Data from the new goal test show support the idea of a lookup table model (specific or general) (Dienes & Fahey, 1995, 1998; Lane et al., 2007). While performance of the long training condition at the new goal test did not decline significantly from performance at practice, participants were slower to respond when the goal was changed. One explanation for the additional time needed to respond is that participants applied a transformation to the lookup table (e.g. add 100 to the input for any given output-input pair).

Dienes and Fahey's model (1995, 1998) suggests that the lookup table is implicit, or inaccessible to learners. The data from both the extended range test wagering task and the Table test are in conflict with this notion. Both the long and short training conditions exhibited a pattern of advantageous wagering at an above chance level suggesting at least some awareness of how the task was being performed. That participants in the long training condition wagered more advantageously than those whose training was short could mean that as training increasing, task knowledge becomes more accessible. A similar pattern was seen on the Table test with both groups performing above chance and the long training condition performing better than the short training condition. When the context of the task was changed, participants were still able to perform at an above chance level. This demonstrates some access to knowledge of the task. That Table test performance did not correlate perfectly with performance at practice is in line with Stanley et al.'s (1989) argument that the ability to express knowledge gained through experiential practice lags behind actual task performance.

While Experiment 1 demonstrated that at least with moderate levels of practice, experientially acquired knowledge is represented as a lookup table, Experiment 2 sought to examine the best way to combine direct instruction using a lookup table and experiential practice of the task. Lane et al. (2007) found that providing a lookup table before practice resulted in very good performance on a standard test, but saw performance decline on a transfer and a speeded test. The data from Experiment 2 replicated those results and expanded on them by showing that model-based knowledge was necessary for transfer to new states. The results of Experiment 2

demonstrate that providing model-based knowledge is necessary for a generalizable representation. Without the direct instruction of model-based knowledge, transfer to a new goal is poor and transfer to new states is at chance.

Also, the results of Experiment 2 demonstrated that memorizing the lookup table at the mid-point of practice reduced the costs associated with model-based knowledge seen in Lane et al. (2007). Participants who learned the table before practice demonstrated relatively poor performance on the new goal test. An analysis of their practice phase revealed that these participants spent the majority of the trials at three states (5000, 6000, and 7000). This limited exploration of the problem space (Newell & Simon, 1972) may have limited the amount of experiential knowledge acquired making it more difficult to transfer their knowledge to the new goal. Those who learned the table after practice performed no better than the No-Table training condition on the speeded test. Thus it would seem that practice after direct instruction is needed if the learned material needs to be deployed quickly, which is consistent with Anderson's (1983) ACT-R model in which declarative knowledge becomes procedural knowledge with practice.

The results of experiment have implications for pedagogy. Proponents of instruction through experiential practice, or discovery learning as it is often called, cite social constructivism literature (e.g. Vygotsky 1978), arguing that information is more easily learned and transferred to new topics when the learner is an active participant in the learning process (Bruner, 1961, Von Glasersfeld, 1989). Mayer (2004) challenged the notion that pure discovery methods of instruction are superior to other types of instruction. In his review of the literature, he consistently shows that guiding learners (e.g. providing learners with information about the task) consistently produces superior

results (e.g. learners remember more or produce fewer errors). One particularly important claim of discovery learning proponents refuted by Mayer is that discovery learning leads to superior transfer of knowledge to new situations (Kittle, 1957, Gagne & Brown, 1961, Shulman & Keisler, 1966).

The results of Experiment 2 clearly demonstrate that direct instruction in addition to experiential practice results in superior performance on the original task, transfer to a new goal and new states, and when time to respond is limited. While direct instruction at any point during training was far superior to experiential practice alone, the best results were obtained when the direction instruction was scheduled for the mid-point of the practice phase. This allowed for full exploration of the problem space as well as sufficient practice deploying the model-based knowledge. This instructional model may be best when the learner will be required to apply the knowledge in a wide variety of situations and under time pressure. One example might be training for pilots who fly in a variety of conditions and are often called on to make split-second decisions. The advantage of combining model-based knowledge with experiential practice has been demonstrated in the literature before (Mathews et al., 1989; Sallas et al., 2006). The results of experiment 2 expand on this by demonstrating that the point at which the model based knowledge is introduced has an effect on performance.

While these results may generalize to all types of learning, they are particularly relevant to situations in which knowledge needs to be applied quickly and across a wide range of situations. For example, pilots learn to fly in one type of airplane, but need to transfer that knowledge across many planes. Additionally, they need to be able to use their knowledge of landing procedures learned on their home airport, and apply it to

landing strips which they have never seen before. Pilots must use their knowledge to make mission critical decisions very quickly. The difference between mediocre and good performance when time to respond is limited could be life and death. Training for pilots and other professionals who are expected to deploy their knowledge quickly and across a wide variety of situations would likely benefit from an instruction schedule which includes direct instruction bookended by experiential practice.

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VITA

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