2002

The effects of implicit, explicit, and synergistic training on learning an artificial grammar

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THE EFFECTS OF IMPLICIT, EXPLICIT, AND SYNERGISTIC TRAINING ON LEARNING AN ARTIFICIAL GRAMMAR

A Thesis

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Arts

in

The Department of Psychology

by
Thomas James Domangue
B.A., Nicholls State University, 1998
December 2002

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Abstract

Participants were trained to generate exemplars of an artificial grammar by bubbling-in letters from exemplars (implicit training), observing a diagram of the grammar then reproducing it (explicit training), or tracing the path of exemplars through a diagram of the grammar (synergistic training). Performance was measured using a cued-generate task. It provided a template for an exemplar with two letters filled in. Participants attempted to generate exemplars that fit the template. The computer corrected the exemplar when it matched at least 70% of the letters in a valid string. Results showed that both explicit and synergistic training led to generation of better quality exemplars (closer to 100% match). However, implicit and synergistic training led to generating more exemplars good enough (at least 70% match) to fit into a wide variety of contextual cues. The author concluded that for both quality and generativity of exemplars synergistic training seemed the most beneficial.

Introduction

Humans have been successful in adapting to their changing environment because of their ability to extract complex information from the environment and utilize it in a beneficial manner (Mathews & Roussel, 1997). It has been widely accepted by researchers that humans acquire knowledge through two separate and distinct modes (Berry & Dienes, 1993; Lewicki, 1986; Mathews, Buss, Stanley, Blanchard-Fields, Cho, & Druhan, 1989; Reber, 1993). The most commonly and better understood learning mode has been termed explicit learning. Explicit learning is the conscious acquisition of rules and processes that govern a complex system or structure within one's environment (Reber, 1993). Many everyday activities from giving directions to a specific location to the proper sequence of steps used in solving algebraic equations (Dienes, Broadbent, & Berry, 1991) are taught through the explicit mode. Explicit knowledge can be verbalized easily (Mathews et al., 1989); therefore, it seems ideal for lecturing about important information, which can then be passed down to succeeding generations.

In contrast, implicit learning is the non-conscious (Lewcki, 1986) and unintentional (Servan-Scheiber & Anderson, 1990) acquisition of information from the environment that enables someone to accomplish certain complex tasks and skills (Reber, 1993). Some researchers assert that implicit knowledge is acquired through the abstraction of memory representations of experiences (Cleeremans, 1993; Mathews & Roussel, 1993; Servan-Schreiber & Anderson, 1990). Probably the most commonly cited example of implicit learning is that of an infant acquiring the language spoken in its household and its subsequent production of novel grammatical utterances without understanding the rules that govern the grammar (Dienes, Broadbent, & Berry, 1991).

Implicit knowledge was once believed to be “totally beyond conscious awareness” (Lewiciki, 1986), and unable to be verbalized (Reber, 1967). However, some researchers (Dulany, Carlson, & Dewey, 1984; Mathews, et al., 1989; Perruchet & Pacteau, 1990) have demonstrated that some implicit knowledge can be verbalized but that not all knowledge can be communicated to others. Thus, it would seem that implicit knowledge about important information or skills would be difficult to pass on to succeeding generations strictly through lectures or explicit instructions. However, implicit knowledge is gained through experience with a particular domain’s structure so that, if one had guided practice with a mentor, knowledge and skills could be passed on through this apprenticeship method.

The purpose of this study was to explore the extent to which implicit and explicit training lead to generative skill using an artificial grammar. Possible synergistic effect(s) of implicit learning and explicit learning were explored by measuring the generative ability of participants who experienced various combinations of training on an artificial grammar. Generativity, as Corballis (1991) defined it, is the ability to take a set of components and, by abiding by a set of rules, produce an unlimited number of instances representative of a particular domain. Corballis also noted that the chief requirement of a mind capable of generativity is the ability to parse a stimulus domain into reusable parts that can then be recombined in constrained but novel ways. Hence, the ability to form linguistic representations and mental representations of objects and scenes has aided human evolution through an environment, which has gotten progressively more complex (Corballis 1991).

George Miller (1969) seems to be the first researcher to use generativity in the investigation of the acquisition of implicit knowledge. In 1958 George Miller, interested in natural language acquisition, attempted to teach participants an artificial grammar through purely inductive processes (Miller 1969). He had participants attempt to generate grammatical letter strings produced by an artificial grammar without prior observation of any valid letter strings or the grammar. One of Miller's cover stories led participants to believe that an ancient writing system had been discovered and that their task was to take the letters from this ancient system and attempt to discover allowable letter sequences. Participants were then told that there was an infinite number of letter strings and to try and generate as many as possible. After each string was generated (hand written) by a participant, the experimenter would look at it, determine its grammatical status and then told the participant whether it was grammatical or ungrammatical. The participants in Miller's study did not learn to generate many letter strings that conformed to the complex set of rules that governed their construction. Miller summed up the results of his experiment when he said, "… a person who is told twenty or thirty times in a row that he is wrong has an understandable urge to strangle the experimenter" (p 144).

Miller admitted that his paradigm suffered some technical problems. The first problem of concern was experimenter error. There were times when an experimenter would inspect a string generated by the participant and deem it ungrammatical when in fact it was grammatical and vice versa. Even though this kind of error may not have happened very often, Miller contended that it had a serious effect on learning because of the sensitivity of the inductive rule learning system. A second concern was that an experimenter would inadvertently provide the participant with too much information through his tone of voice. Miller tried to overcome this obstacle by using flashing lights to indicate whether a letter string was grammatical or ungrammatical. Unfortunately Miller conceded any hesitation on his part to determine the grammatical status of a letter string could have provided a clue to the participant that may have been falsely or correctly adopted. To correct these problems and remove the frustration of his participants Miller believed that “heroic measures” would be needed.

Miller discontinued this line of research stating, “Surely we have here discovered the most inaccurate way to teach a set of rules – the way of pure induction – almost beautiful in its unadorned ugliness” (p 163). Ironically, Miller stressed the importance of studying and understanding the conditions under which implicit learning through inductive processes is accurate because he believed that a good part of learning occurs in this manner (Miller 1969). He also speculated that someone in the future would have more patience and a better method of studying such processes.

In the late 1960s Arthur Reber began researching implicit learning processes through the use of the artificial grammar paradigm (Reber, 1967; Reber, 1969). Reber had one group of participants memorize a subset of grammatical letter strings generated from an artificial grammar. He had a second group of participants memorize a set of letter strings constructed from the same letters used in the grammar but did not abide by the grammar’s rules. Before testing, all participants were informed of the existence of the complex set of rules but not informed as to what they were.

The acquisition of implicit knowledge was then measured through the use of a discrimination test. The discrimination test had participants observe one letter string at a time and make a grammatical judgment about it. If the participant felt that the letter string conformed to the rules of the grammar, then the letter string should be deemed grammatical. However, if the participant felt that the letter string violated one or more rules of the grammar, then the letter string should be deemed ungrammatical.

Reber discovered that the group which was exposed to the letter strings governed by the complex set of rules, therefore displaying structure, performed significantly better during the discrimination test. The group that was exposed to the letter strings displaying the same surface features but lacking the grammatical structure performed significantly below chance. Reber concluded that the group exposed to the grammatical letter strings had abstracted the underlying structure of the grammar and used this knowledge to guide their grammatical judgments.

Since Reber's first investigations into implicit learning processes (Reber, 1967; Reber, 1969), the discrimination test has been by far the most commonly used measurement of implicit knowledge acquisition (Dienes, Broadbent, & Berry, 1991; Gomez & Schvaneveldt, 1994; Knowlton & Squire, 1994; Manza & Reber, 1997; Mathews et al., 1989; Perruchet & Gallego, 1997). As stated above, the predominant artificial learning paradigm employs two phases: a training phase and a testing phase. During a typical artificial grammar-training phase, at least two groups are exposed to a subset of grammatical letter strings. The first group is led to believe that they are participating in a short-term memory experiment. They are told to memorize (implicit training) as many of the letter strings as possible. The second group is given the same subset of grammatical strings and told that they were generated by a complex set of rules and that their job was to try and discover those rules (explicit training).

During the discrimination test phase, participants are shown a set of letter strings one at a time, half of which are grammatical and half are ungrammatical. They are then asked to judge which strings are grammatical and which are ungrammatical. The recurring result is that the participants asked to memorize the letter strings (implicit training) perform better than the participants searching for the underlying rules (explicit training) (see Reber, 1993 for review).

The discrimination test was designed to make the task easier, so that learning could occur and be measured in the short time frame of an experimental session (one to two hours). While this was a valuable step forward in being able to study artificial grammar learning, it is a very artificial static test of grammatical knowledge use. Mathews and Cochran (1997) recently instituted a new type of generativity test that appears to have more ecological validity for language learning. They called it the "generate test" and later modified it to the "cued generate test".

The generate test provides participants with a series of dashes appearing on a computer screen. The number of dashes represents the number of letters in the string that a participant is being asked to generate. This places constraints on which letter strings can be generated. A participant would then type the letters from left to right that is believed to generate a valid letter string. When the participant has filled in the last dash on the right, the enter key is pressed. The computer then leaves the letters that appear in the correct location of a valid string and erases the rest. When the participant's response is close enough to a valid string (70% matching letters), the computer corrects the string. This is a type of "motherese" which does not require the participant to generate a perfect letter string before being successful on each trial (Berger, 1994). The participant proceeds typing in letters for the dashes that were not correctly filled and again presses the enter key. This process is repeated until the letter string is a 70% or better match to a not yet generated valid letter string. The valid letter string provided by the "motherese" program is then shown on the screen to the participant. It is then removed from the memory bank so that it can not be generated again in the same session. The participant is then allowed to proceed to the next letter string template. The cued generate test is exactly like the generate test but it begins by randomly placing two letters in their correct location within the template. These cues force the participant to generate strings from a broad range of valid strings generated by the grammar.

Feedback in the form of the motherese is a more natural way of learning the constraints of a complex domain. This is analogous to not requiring a child to produce a word perfectly before the mother provides it aid in proper pronunciation (Plotnik, 1997). Thus, the mother provides the child the opportunity to explore a wide variety of sounds. This is what the generate test and cued generate test provide. These tests give the experimenter a method of testing a broader range of a participants' limited grammatical knowledge and their ability to use it to meet the demands (cues) present in their environment.

While researchers have sought pure implicit and explicit training methods, the standard memory versus rule discovery manipulation has fallen short of this goal (Mathews, 1997). In the process of memorizing sets of letter strings, participants may employ explicit strategies such as chunking or organizational strategies (Whittlesea & Dorken, 1993) which may lead to the explicit discovery of regularities (rules). On the other hand, participants engaged in explicit rule discovery strategies are exposed to sets of valid strings which may lead to implicit learning (Reber, 1989), or participants may feel they can not discover rules and revert to implicit learning processes (Reber, 1993).

The present study employed a purer explicit training task that had participants observe and then reproduce the actual grammar used to generate the test strings. It also employed an implicit training task that required participants to fill in bubble sheets with the letters of each valid training string. This task allowed little motive or opportunity to consciously search for rules. Finally, a new type of synergistic training task was used. It was termed "synchronized synergy" training. It had participants trace the path of a letter string through a diagram of the grammar by writing each letter into a box located at the appropriate transition point. This task simultaneously exposed participants to instances of the grammar (implicit learning) and relevant knowledge about its structure (explicit learning). These training tasks will be described extensively in the procedure section.

A review of the few studies conducted using a generativity measure of implicit and explicit knowledge acquisition will be presented next. Then a review of the studies done on the possible interactions of implicit and explicit learning will be summarized. Prominent theories on implicit learning will then be presented and their positions on generativity and interactions between the two learning modes discussed.

Review of Literature

Review of Generativity Studies

Mathews and Cochran (1997) reported two experiments that were aimed at overcoming the obstacles encountered in George Miller's (1958) investigation into the generative processes of natural language acquisition. They believed that Miller's problems stemmed from the seemingly meaningless generation of letter strings that participants perceived as boring. Mathews and Cochran devised a cover story that was aimed at reducing boredom and providing a meaningful element to the experimental procedure. They also had the benefit of technological advances, which made the process more reliable.

Participants in Mathews and Cochran's (1997) Experiment 1 were given a cover story that had them in a starship. There were two groups. Both groups were told that they were to generate poison food labels (valid letter strings) so that cans of contaminated food could be discarded. Participants in the first group were given explicit task instructions. They were told that there were spies on the starship and that the spies contaminated the cans of food. These participants were instructed to look for common rules or patterns contained in the valid letter strings that they had generated up to this point. Moreover, they were told that this could help break the code that the spies used to identify which cans of food were poisoned.

Participants in the second group were given the implicit task instructions and were led to believe that the poisoning of the food was accidental. They were told to try and commit to memory the valid letter strings that they had generated up to this point. They were led to believe that this strategy was productive because all the poison food labels (valid letter strings) looked very similar and this could facilitate their finding more poison food labels.

Mathews and Cochran implemented the motherese program that helped participants in the discovery of poison food labels on the generate test. As described earlier, the generate test presented participants with a series of dashes on a computer screen. Each dash represented a letter within a string. Participants typed in a letter for each dash and then pressed the enter key. The letters that corresponded to the correct positions that they appeared in valid letter strings would remain on the screen and all others were erased. The participants continued this procedure until they had typed in at least a 70 % match of a not yet generated valid letter string. When a 70 % match was generated, the program would go into the data bank of 43 grammatical strings (generated by Reber's 1967 grammar) and present on the screen the corrected valid string. At this point, participants given explicit instructions would observe the corrected valid string and look for common rules or patterns among the strings they had generated thus far. Participants given the implicit instructions would attempt to commit to memory each valid string they generated during the session. As mentioned before, after a valid letter string was presented on the screen for observation, it would be discarded from the data bank and could not be generated again during the same session.

Participants attended three 25-minute sessions during which they attempted to generate all 43 valid letter strings (poison food labels). They received no prior exposure to any letter strings or to the grammar. During the third session, participants averaged 246 attempts at generating valid strings but only 5.5% of those attempts produced at least a 70 % match. It made no difference if the participants received the implicit instructions or the explicit instructions. The generate test reproduced the common finding that participants perform poorly if they are not exposed to instances prior to testing (Reber, 1989; Reber, 1993).

Mathews and Cochran's (1997) Experiment 2, on the generative properties of artificial grammar learning, was modified. The first change was to employ the artificial grammar used by Mathews et al. (1989). This grammar generates 177 valid letter strings. The second change was to present the participants with a training phase that allowed them to see 30 valid letter strings generated from the grammar before attempting to generate strings. There were five training conditions and two types of tests.

During the training phase, each of the 30 valid letter strings appeared on the computer screen one at a time for 3 seconds. The screen then went blank and a series of dashes appeared. These dashes matched the length of the letter string just presented. However, what part of the letter string the participants were to type depended upon which training condition they were assigned to.

Participants who received "whole recall" training observed a letter string presented on the computer screen. When the screen went blank and dashes appeared, they attempted to reproduce the letter string exactly as they just saw it. Participants who received "familiar fragment finding" training were instructed to search the strings for familiar (recurring) letter patterns. When the screen went blank and dashes appeared, they typed in chunks of letters up to six characters long. Participants who received "familiar fragment yoked" training were told that they were yoked to a partner in the familiar fragment finding training condition. They were presented valid letter strings with the chunk typed in by their partner highlighted. When the screen went blank, they were to type the highlighted chunk that they just saw. Participants who received "random fragment yoked" training were yoked to a partner in the familiar fragment finding training condition also. However, they were presented valid letter strings with randomly chosen chunks highlighted. The highlighted chunk was the same size as their partners'. When the screen went blank and the dashes appeared, they typed only the chunk that was highlighted. Finally, participants who received "informed fragment finding" training performed the same task as the familiar fragment finding training group, but they were given the spy cover story. Hence, they were instructed to engage in rule discovery strategies (explicit training). All other groups were given the memorization (accidental poisoning) cover story (implicit learning).

After the participants finished their training phase, half of the participants in each group took a discrimination test and the other half took a string generation test. The participants who took the discrimination test were shown 120 letter strings and asked to judge whether each was a poison food label (grammatical) or not a poison food label (ungrammatical). The string generation task required participants to generate 100 letter strings believed to be poison food labels.

The results showed that exposure to a subset of valid instances facilitated the participants' generative abilities greatly. Whereas participants not shown instances in Mathews and Cochran's Experiment 1 had a "hit rate" (proportion of attempts producing at least a 70% letter match) of 5.5%, participants shown instances prior to testing in Experiment 2 had hit rates between 30% and 40%. The result of most importance to this experiment was that the pattern of results on both the discrimination test and generation test were very similar. Participants in all groups except the random fragment yoked group performed well on both the discrimination test and generation test. Thus, it appears that implicit training (e.g. whole recall training) led to performance equal to the explicit training (e.g. informed fragment finding training).

Mathews, Roussel, Cochran, Cook, & Dunaway's (2000) Experiment 1 addressed the issue of participants' poor performance when instructed to search for rules (see Reber, 1993 for a review of these cases). Reber (1993) asserted that the reason participants in rule discovery conditions perform poorly is because they do not know what type of rules to look for. Participants in this experiment were given paper and pencil (cognitive artifacts), and instructed on what type of rules to look. Moreover, they were told what approach would be most beneficial. These instructions were given to eliminate the notion of participants' inability to discover rules (explicit learning condition).

Mathews et al. (2000) also gave meaning to the individual letters of the grammar in hopes that this would provide more meaning to the cover stories. The extension of the previous cover stories had letters corresponding to a decontamination chamber(s). Cans of food were passed through a series of decontamination chambers but unfortunately not all chambers were functional. If a can of food passed through only non-functional chambers, it would bare a poison food label (valid letter string). Participants were trained on how they could discriminate poison food labels from non-poison labels and how to generate a list of poison food labels.

The same artificial grammar used by Mathews and Cochran's (1997) Experiment 2 was used. Participants in the explicit learning condition were given 88 valid strings, paper and pencil, and instructed on how to discover the rules of the grammar. They were also shown a video tutorial on how to build a model of the grammar (a transition diagram) from integrating two valid letter strings into a schematic diagram. The model was intended to illustrate the relationships between letters (rules). These participants were called "model builders". Participants in the implicit learning condition were also given 88 valid strings and paper and pencil to help them in their memorization-training task. These participants were referred to as "memorizers".

The training phase consisted of three 1-hour sessions. During each session, participants performed their study tasks for 30 minutes followed by their practice-test for 30 minutes. Half of the participants in the explicit training condition (model builders) performed a discrimination practice-test on the 88 strings observed during their study phase and on 88 lures (ungrammatical strings). The other half of the model builders attempted to generate the 88 valid strings seen during their study phase. For the generate practice-test the computer only recognized the 88 strings used during the study task. The participants in the implicit training condition (memorizers) were also split into two groups for their practice-tests and instructed the same as the model builders.

After a sequence of three sessions of study phases followed by practice-tests was completed, a one hour final-test was conducted. Half of the participants from each of the four groups (model builder/discrimination, model builder/generate, memorizer/discrimination, memorizer/generate) performed either a discrimination test or a generation test. All 177 valid letter strings were used for the final test. The model builders were allowed to use their models during the final test.

The results of the final discrimination test showed that the participants who were memorizers/generation performed better than all groups. Model builders/generation performed second best. On the generation test, the memorizers/generation generated significantly more (64% of available valid strings) strings that met the 70% criterion than all other groups. However, this score does not take into account the number of attempts it took them to generate these strings. Therefore, the hit rates (described above) of the participants' were examined. When looking at the data in this manner, the memorizers/generate had a hit rate of 71% which was significantly higher than all other groups. However, the memorizers/discrimination performed second best (57%) when looking at the data in this manner.

Mathews et al. concluded that the difference came from the memorizers/generation practice test generating the prefixes (up to five characters in length) of the letter strings correctly on 95% of their attempts. This was significantly higher than all other groups. They also looked at the quality of letter strings as the final test proceeded. Interestingly, the quality of the strings (how close to a perfect string) did not diminish significantly through the session. Mathews et al. asserted that this was evidence that the participants are learning the grammar's "constraints and allowable transformations" and not rote memorization.

In Experiment 2 of Mathews et al. (2000), the generate test was modified to resemble a "more reasonable measure" of generative knowledge. The modified test was called the cued generate test. The cued generate test was basically the same as the generate test with one exception. Instead of having to replace all the dashes with letters to generate a string that met the 70% criterion, the cued generate test provided three cues (letters randomly placed in their grammatically correct position). The participants had to generate a string that fit the template set down by the dashes and letters. The 70% match criterion was still required before a participant could proceed to another string.

Mathews et al. reasoned that this was a more natural measurement of generative knowledge because in natural settings, the response one makes depends upon the cues one encounters. For example, one would respond to the demands of a professor in a very different manner than one would respond to the demands of a friend. Plus, the response would be tailored to the particular occasion or context.

All participants in Experiment 2 received the memorizers' (implicit training) cover story of cans of food being accidentally poisoned. The letter strings were typed unto rolodex cards and were presented to the participants as either a "free to organize" study list or as "fixed" study list bounded to a base. The organize condition and the fixed condition. Half of the participants in each condition received a study list consisting of 22 valid letter strings or a study list consisting of 88 valid letter strings. Therefore, there were four groups representing all combinations of organizational type and string set length.

All participants experienced one session. The training phase lasted 20 minutes. Participants in the organize group freely manipulated, categorized, and organized the letter strings any way they felt would facilitate their memorization. The fixed group attempted to memorize as many of the letter strings as possible without the benefit of manipulation. During the 20-minute test phase, participants took the cued generate test and attempted to generate valid letter strings.

The first result of interest was that there appeared to be no beneficial effect to being exposed to a larger set of valid letter strings. The freedom to organize the letter strings was approaching significance. The organize-short letter set group performed best and the organize-long letter set performed second best. However, when it came to the hit rate, there was a significant interaction between organizational type and list length. The organize-short group generated significantly more valid letter strings than all other groups with a hit rate of 57%.

Mathews et al. concluded that the free to organize short list group performed best according to either measure. Moreover, Mathews et al. speculated that "…organizational processes might enhance development of generative knowledge… "(p 170), and "…we believe that the development of generative knowledge involves a synergistic interaction between implicit and explicit learning" (p 172).

There have been too few experiments that have addressed the question of interactions between implicit and explicit learning and possible benefits or hindrances (Reber, Kassin, Lewis, & Cantor, 1980; Mathews et al., 1989). It seems like there is a gap in the literature regarding such interactions. Humans use both modes of learning, and it seems safe to say that interactions between the two modes do occur. Reber et al. (1980) have asserted "In everyday life, people do not learn about their environment in strictly implicit or explicit ways, but rather as some blending of the two" (p 493). Kersten and Earles (2001) echoed this view. They said that current research in second language acquisition supports the contention that both instruction (explicit learning) and experience (implicit learning) are needed to successfully attain all levels of knowledge about the second language.

It is important to conduct research on the interaction(s) of implicit and explicit learning. Moreover, it is important to seek the optimal combination of these two modes of learning (henceforth termed synergy or "synergistic effect") so that the results could be applied in organizational and educational settings (Mathews et al., 1989). A few researchers have already made the venture into this type of exploration; however, the studies are few and some results are contradictory (Reber et al., 1980; Mathews et al., 1989). The different findings may have occurred because these studies used different artificial grammars and testing procedures.

Review of Studies on Interactions

What seems to be the first experiment (Reber et al., 1980) that investigated possible synergies between the two learning modes deviated from the traditional paradigm by presenting some participants with more than one type of training task during the study phase. There were five training sequences in this experiment. The first group experienced only the implicit training task (I group), the second group experienced only the explicit training task (E group), and the combination groups experienced implicit/explicit training, explicit/implicit training, and (IEI) training.

During the study phase, the explicit training task required participants to generate (write on paper) three letter strings from a diagram of the artificial grammar each four, six, and eight letters in length. The diagram was removed before testing began. The implicit training task required participants to observe a set of 21 valid letter strings that were flashed on a screen for seven seconds each. This set was randomly repeated three times for a total of 63 observations. Participants were told to simply observe the letter strings for a later memory test. They were not told of the repetition of letter strings.

Before the test phase began, the groups that experienced the implicit training were informed that the letter strings shown were generated by a complex set of rules. All participants were then asked to perform a discrimination task on more strings. They were presented 25 grammatical and 25 non-grammatical strings. This set of 50 strings was randomly repeated twice without the participants' knowledge.

Reber et al. concluded that any blending of the two learning modes was significantly better than either learning mode alone. Moreover, the explicit/implicit group was significantly better than all other groups suggesting that a mental representation of the structured domain (rules) followed up by some valid instances would be the optimal learning sequence. Concerning the better performance of the combination groups, Reber et al., (1980) suggested, "… this should not be too surprising for this is the way in which knowledge of most complex environments is acquired" (p 501). It is worth noting that even though the group who received only implicit training (I) performed worse on the grammatical judgments, they had significantly faster response times than all other groups. Two experiments conducted by Mathews et al., (1989) also explored which sequence of implicit training and explicit training was most beneficial. The experiments deviated from the traditional artificial grammar learning experiment by having participants correct ungrammatical letter strings during the training phase. The second experiment also used a bi-conditional grammar (described below) instead of a finite state grammar.

In Mathew et al’s (1989) Experiment 3, the explicit training was called “the edit task”. The edit task required participants to observe ungrammatical letter strings. They were told that these were “flawed” strings. Participants were informed that the strings were generated by a complex set of rules and that their task was to learn these rules to determine what was causing them to be ungrammatical. Participants marked the letter(s) that they thought flawed the string. After they marked the letter(s), the correct string was displayed as feedback. Therefore, they were able to continuously test hypotheses about the grammar’s rules.

The implicit training task was termed “the match task”. During the match task, participants were shown a valid letter string on the computer screen and asked to hold it in memory. The screen went blank for 2 seconds then five strings were displayed. The participant was asked to select the one held in memory. The strings ranged in violations form 1 to 4 letters. After the selection was made, the computer provided feedback by displaying the valid string.

There were five groups in the experiment and each experienced 100 sets of five strings during the training phase. The edit group performed the edit task on all 100 sets, the match group performed the match task on all 100 sets, the match/edit group performed the match task on the first 50 sets followed by the edit task on the remaining 50 sets, the edit/match task performed the edit task on the first 50 sets followed by the match task on the remaining 50 sets. The alternate group alternated training tasks after each response through the 100 sets.

At the beginning of the testing phase, all participants were informed that the letter strings they had just seen were generated by a complex set of rules. Participants were shown 100 sets of five strings and asked to choose the grammatical string. For the first 70 trials participants did not receive feedback. Beginning with trial 51 the letter set was changed but the grammatical rules remained the same (transfer test), then on the 71st set, feedback on performance was provided to the participant.

The results revealed that there was no benefit to having either the edit task (explicit training), the match task (implicit training), or any combination of the two tasks (synergistic training). Mathews et al. concluded that explicit training (the edit task) played no additional role in the acquisition of knowledge about the artificial grammar. Also, the performance of all groups dropped dramatically when the letter set was changed; however, all groups still performed above chance. This was interpreted as evidence of the acquisition of abstract knowledge of the grammar’s rules. Mathews et al concluded that implicitly acquired knowledge alone was sufficient to acquire knowledge of a finite-state grammar and that a combination of training tasks did not produce a synergy. However, Mathews et al’s Experiment 4 did demonstrate a synergistic effect between implicit and explicit learning when a bi-conditional grammar was used.

Experiment 4 of Mathews et. al., (1989) used the same design as Experiment 3 with the exception of the type of grammar used. In this experiment a bi-conditional grammar was used to generate the letter strings. A bi-conditional grammar is based on simple logical rules that should be more accessible to the explicit learning mode. The strings generated by the bi-conditional grammar were eight characters in length with a period separating the first four letters from the second four letters. Also, there were six different letters and three correspondence rules that determined which letters could occur in relative positions in each half of the string. For example, if a letter from one pair appeared in the first position, its corresponding letter must appear in the fifth position. The letters corresponding to each other were: X went with T, P went with C, and S went with V. An example of a valid string would be CTTV.PXXS.

The results showed that there was a significant synergistic effect. The match/edit training condition performed significantly better than all other groups. The edit group, the edit/match group, and the alternate group performed significantly better than the match group, which performed significantly worse than all other groups. When the letter set was changed (transfer) on the 51st set, the same synergistic effect pattern was observed. Thus, experiencing both types of training methods seemed to be beneficial. Mathew et al. asserted, "… we suspect it may have considerable generality, given that most real-world tasks seem to involve both memory-based and model-based knowledge" (p 1098).

Theories of Implicit Learning

IPA Theory

The internal processing algorithm (IPA) theory used to explain the acquisition and utilization of implicitly acquired knowledge was proposed by Pawel Lewicki. An IPA is said to be "…the memory representation of covariation between two or more features or events [within one's environment] … (p 29)" (Lewicki, 1986). The construction of IPAs is hypothesized to be an omnipresent and totally nonconscious process (Lewicki, 1986). Moreover, IPAs are believed to be responsible for the development of one's cognitive dispositions (e.g. phobias) and personality traits (Lewicki, Czyzewska, & Hill, 1997).

There is no way to tell when, where, or how an IPA or "cognitive algorithm" was formed. IPA theory states that once an IPA is developed, there is no way to change or control it through conscious processes. In fact, the only way one can discover the existence of an IPA is through direct, systematic observation of one's behavior(s) (e.g. preferences, feelings, emotions, phobias) in an attempt to uncover the cues that provoked the response(s) (Lewicki, 1986).

After an IPA is developed, it guides one's judgments and decisions concerning everyday interactions with the environment (Lewicki et al., 1997). IPAs are said to be personal and in control of what one finds "funny", "sad", or "emotionally moving". Thus, each IPA has to remain in a constant state of "functional" readiness (Lewicki, 1986).

The IPA theory does not lend itself to generativity as Corballis (1991) defined it. Since, IPAs are wholes and not made up of components, which could be recombined to generate different responses, they do not possess any generative abilities. All IPAs are said to be "fixed". Thus, novel responses in any context are never performed using implicit knowledge.

IPA theory leaves little doubt about any possible interactions between implicit learning processes and explicit learning processes. Lewicki's (1986) IPA theory asserts that "The fact that the IPA is nonconscious in all aspects of its acquisition and subsequent operation constitutes its distinctive central feature" (p 32). Therefore, it seems safe to conclude that according to this theoretical approach to implicit learning, there are no synergistic effects between the two learning modes.

Abstractionist Theory

Abstractionist theorists contend that acquisition of implicit knowledge occurs through the induction of rules governing the construction of a complex structured domain without conscious reflection to do so (Reber, 1989). The abstraction theorists provide evidence for this view through the numerous studies that have demonstrated transfer (Knowlton and Squire, 1994; Mathews et. al., 1989; Reber, 1969). Transfer is the ability to continue applying knowledge correctly when the surface structure (letter set in artificial grammars) is changed before the testing phase but the underlying rules (the same artificial grammar) remain the same (Reber, 1969). The ability of transfer has the abstractionist theorists believing that the underlying rules from the grammar were learned and not just surface structure similarities (Mathews et al., 1989; Reber, 1969).

The abstractionist theory is the oldest view concerning how implicit knowledge is acquired (Reber, 1967). In the beginning the abstractionist theory (Reber, 1969) contended that implicit learners acquire implicit knowledge because they formed a (nonconscious) mental representation of the rules used by the researchers to generate the letter strings. This representative knowledge was said to be acquired, stored, and used to guide responses.

Further research using transfer studies has provided evidence that along with abstracting the underlying rules of the grammar, participants seemed to be storing instances of the training set (Manza and Reber, 1997) or imperfect memories of letter strings (Mathews, 1991). Mathews contends that the imperfect memories are memories of partial strings. Participants in Mathews et al.'s, 1989 study were able to verbalize bigrams, trigrams, (two and three consecutive letters respectively) and runs (same letter repeatedly) in valid letter strings. These partial memories were mostly of beginnings, endings, and runs in the middle of strings. They asserted that even though participants did gain some knowledge of chunks of strings that this knowledge was not useful unless the spatial location of these partial memories were also known (Mathews, 1991). Mathews (1991) contends that these partial memories taken together with information of their spatial location constitute abstract rules used in the determination of string grammaticality.

Concerning the concept of generativity of implicitly acquired knowledge, the abstractionist theory has no problem accepting it. The abstract rules producing a mental representation and the occurrences of specific instances (Manza & Reber, 1997) and partial memories (Mathews, 1991) could be used to recombine and manipulate rules and memories to generate novel stimuli. This is the essence of what Corballis (1991) meant by generativity.

An abstractionist's view of the possible interactions of implicit and explicit learning is a positive one. In fact both Reber et al., (1980) and Mathews et al., (1989) have conducted experiments investigating such interactions. Reber et al. found that exposing participants to explicit training followed by implicit training produced the best performance. On the other hand, Mathews et al., demonstrated, using a bi-conditional grammar, that exposing participants to implicit training followed by explicit training produced the best performance. The different results are most likely due to the fact that both experiments used different methods and different types of grammar. Yet, both sets of results led to the conclusion that some combination of the two training methods resulted in better performance than either method alone. Mathews et al. termed the positive results obtained from a combination of the two training phases “a synergistic effect”.

Exemplar Theory

Brooks and Vokey (1991) proposed the exemplar theory of implicit acquisition of knowledge. Brooks asserted that when someone is exposed to a representative set of stimuli from a structured domain (valid letter strings in the artificial grammar learning paradigm) that whole exemplars are memorized and stored in memory. Thus, letter strings, in this case, are stored in memory exactly as they are encountered during the training phase with regard to their surface structure. There is no attempt to have them undergo any abstract recoding. During the testing phase, participants observe a string and compare it to letter strings stored in memory. If the participant decides that a test string is a close enough match to a string stored in memory, then the letter string is deemed grammatical. However, if the letter string fails to be similar enough to a stored string, then it is judged to be ungrammatical.

From the view of the exemplar theory, the prospect of generativity of novel letter strings would not be viable. The fact that the exemplar theory encodes and stores whole letter strings precludes it from meeting Corballis’ (1991) definition for generativity. The theory does not account for storing partial letter strings. Therefore, with only whole letter strings stored in memory, there are no individual components to be recombined to generate novel letter strings.

The exemplar theory would predict that there would be an interaction between the implicit learning mode and the explicit learning mode. Through encoding, our explicit knowledge can influence how we encode the stimuli, which impacts implicit learning

(Whittlesea and Dorken, 1993). However, the implicit learning mode would never have any influence on the explicit learning mode because it only creates a data base of strings in memory. Accordingly, the exemplar theory would predict an interaction but only in one direction.

Chunking Theory

The chunking theory of acquisition of implicit knowledge states that when someone encounters a structured domain, such as an artificial grammar, they tend to parse the stimuli (letter strings) into smaller units – chunks. Moreover, sensitivity to a structured domain occurs unintentionally (Servan-Shreiber and Anderson, 1990) and without explicit knowledge of its features – constraints (Perruchet and Gallego, 1997).

Servan-Scheiber and Anderson proposed the theory of competitive chunking.

In the theory of competitive chunking, chunks are said to possess strength. That is, a chunk's strength is determined by the frequency and recency of it being retrieved from memory. Chunks are also said to have support that is based on the strength of the sub-chunks composing the chunk. Chunk strength determines which chunks are created, retrieved, and elaborated on. Chunks can overlap to create new chunks depending upon the strength of the sub-chunks in different chunks. If adjacent sub-chunks from different chunks attain more strength, their support goes to the creation of a new independent chunk.

Perruchet and Gallego, (1997) proposed a similar account of implicit learning called the "subjective unit formation account". Their view contends that participants automatically encode stimuli (letter strings) by parsing them into small and disjunctive chunks. By disjunctive, they meant that certain chunks or as they called them "units" do not overlap one another. A primitive (letter) in a string can only occupy one chunk in the parsing of a particular stimulus. Chunks are created as to have the smallest number of chunks feasible to generate one whole instance.

Perruchet and Gallego (1997) believe that participants in artificial grammar learning experiments do not encode the grammatical rules responsible for string generation. However, they behave as if they had obtained these rules because the rules are partially embedded into the small disjunctive units. Through the numerous chunks possessed by a participant, grammaticality judgments are made.

Both Servan-Scheiber and Anderson’s (1990) theory of competitive chunking and Perruchet and Gallego’s (1997) subjective unit formation account would accept a concept such as generativity of novel stimuli into their framework. The fact that both theories parse stimuli upon encountering them, store the parsed chunks in memory, and retrieve them upon encountering novel stimuli provides for great flexibility, hence, generativity.

As for interactions, the theory of competitive chunking would say that stimuli are unintentionally parsed (implicit) and that knowledge of the method of chunking can be understood through explicit though during retrieval (Servan-Schreiber & Anderson, 1990). Perruchet and Gallego, (1997) contend that consciousness (explicit) knowledge of a structured domain is unnecessary to gain sensitivity of the rules governing its construction. Thus, no interactions between implicit and explicit processes are required.

Overview of the Present Study

The present study attempted to improve on past studies by eliminating as much training task contamination as possible. Cross task contamination occurs when participants engaged in one type of training task (e.g. implicit learning) are exposed to or have the opportunity to acquire knowledge through the other mode (e.g. explicit learning) (Reber et al., 1980; Mathews et. at., 1989). The present study also examined possible interactions between the two learning modes. Moreover, the use of the cued generate test provided a more ecological approach to the study of the human learning processes.

The implicit training task had participants exposed to a set of letter strings and a packet of bubble sheets. The participants took one letter string at a time and copied each letter of the string into a bubble from left to right until the string was completed (a more detailed account of all training tasks is presented in the procedure section). The copying of letters into bubbles was considered to be a task that did not evoke or encourage any rule discovery strategies. Participants were led to believe that their accuracy and the amount of letter strings completed would be measured. Hence, any attempt to intentionally discover common rules across letter strings would interfere with their intended goal – speed and accuracy of bubbling strings.

The explicit training task provided participants with a copy of the actual diagram of the grammar. Participants engaged in this training task were exposed to a minimal number of letter strings during the training phase in an attempt to eliminate opportunities for implicit abstraction of string features. During the training phase, participants observed the grammar diagram and attempted to learn and commit it to memory. Their observation of the grammar was followed by an attempt to reproduce it using pencil and paper. They were told that if they learned the rules to this diagram that they would possess the knowledge to do very well during the test phase. It was observed that by the second of four attempts to reproduce the grammar during the training phase, most participants had perfect reproductions. This led to the conclusion that an explicit mental representation of the rules of the grammar was learned in this condition.

The present study also manipulated the presentation of the training tasks just described. One group received explicit training (grammar diagram) during their first weekly training phase followed by the implicit training (bubble sheet) during their second weekly training phase. Another group received the opposite order of the training tasks. As mentioned in detail earlier, the manipulation of training tasks was investigated previously (Mathews et al., 1989; Reber et al., 1980) with differing results. It was hoped that the present study's attempt at "task purification" would reveal evidence as to which presentation sequence is most beneficial in the artificial grammar paradigm.

The final training task was used in an attempt to achieve further understanding of the interactions between implicit and explicit learning processes. This task was termed "synchronized synergy". During synchronized synergy training, participants were exposed to the same set of valid letter strings used for implicit training and a map of the grammar diagram used for explicit training. Participants took one valid letter string at a time and copied each letter into the proper transition boxes on the map from left to right. It has been proposed that the way to obtain optimal synergy is to develop a training task that requires both the implicit and explicit learning processes to be engaged simultaneously (Roussel, 1998). This task seemed to meet both these criteria.

The cued generate task provided what would seem to be a better and more natural measure of learning than what a simple discrimination test provides. Using the cued generate test a participant can explore a wider range of the structured domain. The constraints that the cues placed on the participants provided a good measure of the flexibility of acquired knowledge. The computer's "motherese" ability to provide feedback for imperfect strings was more like what one encounters in natural settings. A response made by someone in a particular context (e.g. social setting) is greeted with some sort of counter response, which has to be taken into consideration before a proper reply can be made. It is seldom that one encounters situations in the environment requiring interactions that could be completely settled with a simple discrimination judgment. Thus, generativity would seem like a more logical and ecological measurement.

The author predicted that exposure to instances of the grammar would facilitate generativity. Therefore, it was believed that the purely implicit learning group and the synchronized synergy group would generate the most valid strings that met the 70% match criterion. Obtaining an explicit representation of the grammar was predicted to hinder generativity but extremely facilitate the quality generated strings (closer to 10s). Generativity was expected to be hindered because explicit (reflective) processes take longer than implicit (experiential) processes (Norman, 1991). Moreover, implicit processes have been shown to have quicker response times (Reber et al., 1980), so there is more opportunity to generate valid strings through implicit processes than explicit processes.

The groups with the mixed training tasks were expected to do well on all measures but which combination of training tasks would be more beneficial was undetermined because of past results (Mathews et. al., 1989; Reber et. al., 1980). The synchronized synergy group was predicted to perform best overall on all measures because of the integration of both learning modes into one task (Roussel, 1998; Sun, 2002).

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Materials and Method

Participants

One hundred twenty undergraduate students taking a variety of psychology courses at Louisiana State University participated in the experiment. All participants were volunteers who received extra credit for their participation.

Materials

The artificial grammar used by Mathews et al., (1989) and Mathews & Cochran (1997) was used in the present experiment. This grammar generates 177 grammatical letter strings ranging from 5 to 11 letters in length. A subset of 22 valid letter strings randomly repeated 4 times for a total of 88 instances was used for implicit training and synchronized synergy training which will be described below. Each of the 22 strings was typed onto a 1" by 2 ½" label and placed in the center of 2 ¼" by 4" rolodex cards which was bound to a base.

Three diagrams were also used. The first diagram was a copy of the artificial grammar (see figure 1) stapled to a sheet of cardboard. This diagram was used for explicit training. The second diagram was a bubble sheet, which displayed the letters of the grammar vertically along the left side of the sheet and the numbers from one to twelve displayed horizontally across the top of the sheet. Circles intersected each letter and number (see figure 2). This diagram was used for implicit training. The third diagram was a copy of the grammar with boxes placed at the grammar's transition points (see figure 3). This diagram was used for synchronized synergistic training.

Design

The design was a one factor with six levels. Group membership was the between subjects factor. The six groups consisted of a combination of implicit training, explicit training, synchronized synergistic training, and no training (control group) during the two weekly sessions (within subjects' factor). There were six groups: implicit/explicit, explicit/implicit, implicit/implicit, explicit/explicit, synergy/synergy, and control/control. Twenty participants were randomly assigned to each of the six conditions.

Procedure

Participants were tested in groups of up to four. There were two one-hour sessions conducted one week apart. Each session consisted of two phases. During the first phase, participants experienced implicit training, explicit training, synchronized synergy training, or no training. The control group did not receive any training and proceeded straight to the test phase during both weekly sessions.

At the beginning of the first session all participants, except for the control group, were informed that each session consisted of two phases (training phase and testing phase) each lasting 20 minutes. Before the training phase began participants read a cover story devised by Mathews & Cochran (1997) that attempted to eliminate the shortcomings of Miller's (1958) letter string generation experiment. These obstacles were the meaningless of the task of generating letter strings and the boredom that accompanied the task.

The cover story had the participants in a military transport vessel in space. Their job was to try and distinguish cans of food that were poisoned with radioactive material from those that had been decontaminated. Participants were told that the survivors of the destroyed space colony had set up a series of decontamination chambers and had managed to decontaminate some of the cans. Each can of food was labeled with a string of letters indicating which decontamination chambers they had past through.

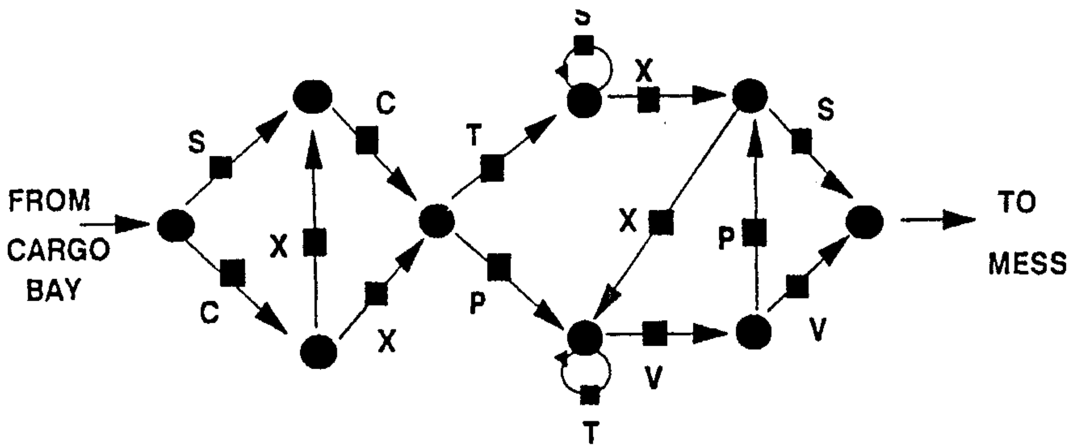

Figure 1. Artificial Grammar Diagram. The artificial grammar used to generate the 177 valid letter strings. Also, the diagram participants performing explicit training observed and then reproduced.

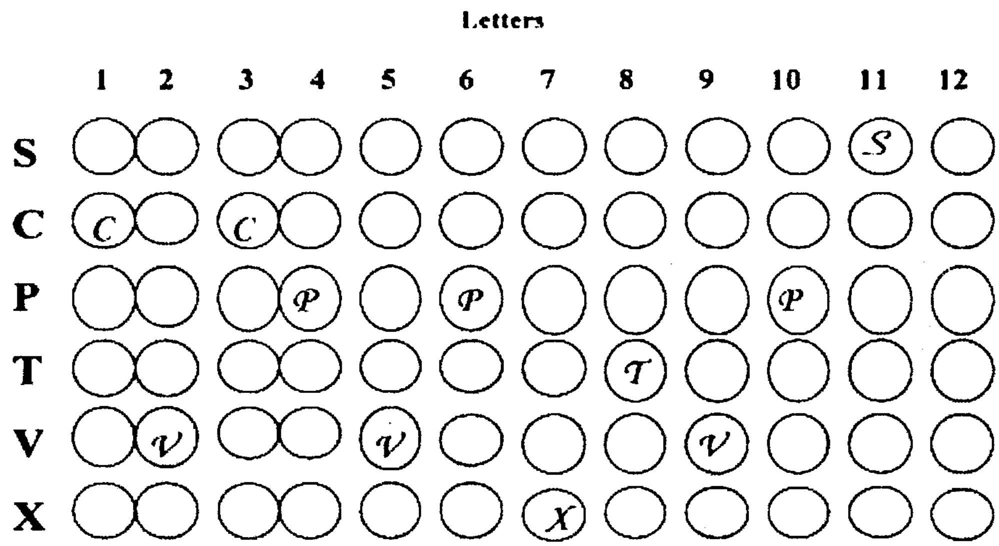

Figure 2. Bubble Sheet Diagram. The bubble sheet used by the participants to perform the implicit training task. The valid letter string CVCPVPXTVPS is inserted to illustrate the proper method used.

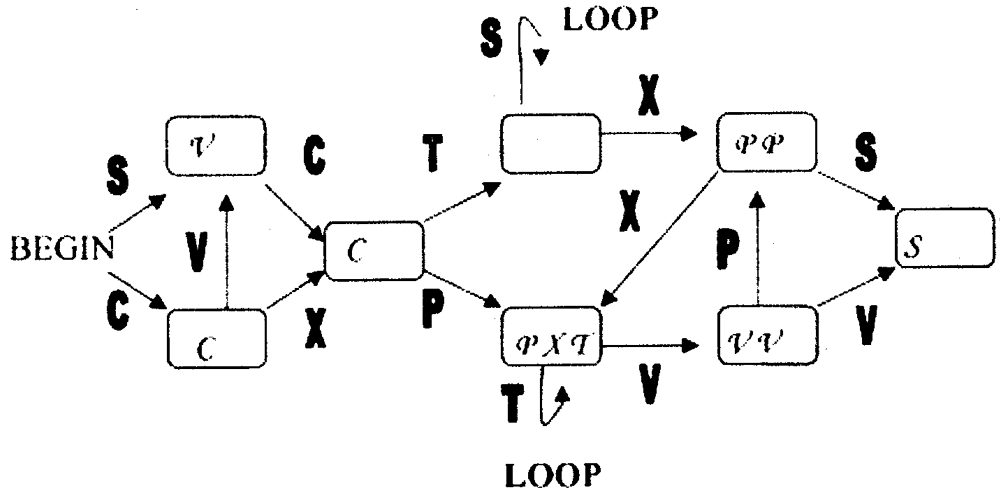

Figure 3. Transition Map of the Grammar. The diagram used by participants in the synchronized synergy group. The valid letter string CVCPVPXTVPS is traced through the map to illustrate the proper method used.

Implicitly trained participants were told that they were to be given a small set of poison food labels (valid letter strings) that had been salvaged; however, there were still many poison food cans left and their labels were similar to the ones they had just seen. Explicitly trained participants were given a diagram of the locations of the decontamination chambers through out the space colony and told that by studying it, they would be able to uncover all the remaining poisoned cans. Participants who received synchronized synergy training were told that they were to be given a small set of poison food labels and a diagram displaying the positions of the decontamination chambers. The mixed conditions received the appropriate instructions before each session. A copy of the exact instructions read by the participants before training can be located in Appendix A.

Training Phase

At the beginning of each weekly session participants were instructed on the proper procedure to their respective training tasks. Participants repeating the same training task were familiarized with the procedure again before beginning. All participants were supplied with the necessary materials for their training and given twenty minutes to complete their assigned task. Any questions were answered prior to starting the timer.

Implicit Training

The implicit training task required participants to copy as many of the 88 instances (valid letter strings) on the rolodex into the bubble sheets in 20 minutes as possible. Along the left side of the sheet each row of bubbles was labeled with a particular letter of the grammar and along the top the numbers one through twelve labeled the columns. Participants copied each letter of the valid string into the bubble that intersected the row labeled with that letter and the corresponding column labeling the ordinal position of that letter within the string (see figure 2).

All participants engaging in the implicit training task were told that it was important to be accurate as well as quick. The rationale for this particular implicit training task was that participants engaged in this activity would have processed the strings with little time or reason to think about how they were generated.

Explicit Training

The explicit training task required participants to observe a copy of the artificial grammar (see figure 1) for 2 ½ minutes then turn the diagram over with the cardboard side up and for another 2 ½ minutes attempt to reproduce the grammar using pencil and paper. The sheet of paper used to reproduce the grammar was taken out of the packet and placed flat on the table to prevent indentation onto the next sheet. This was done to prevent a participant from simply tracing the indentation of the previous drawing. This was repeated four times for a total of 20 minutes of training.

The goal of the explicit training was to teach an explicit representation of the grammar without showing valid letter strings that could stimulate implicit learning. However, it was found during piloting that participants have a very difficult time appreciating the complex structure of the strings generated without having been exposed to a few of them. As a result, participants who had the explicit training had three valid letter strings demonstrated to them regarding what they were expected to perform during the test phase (cued-generate test).

The three valid strings illustrated the increasing complexity of the instances generated by the grammar. The first string demonstrated was **- - T X -**. The strings **SCTXS** and **CXTXS** are the only two correct strings capable of being generated given these particular cues. These cues were used because it is the simplest and should have been easily understood. The second string demonstrated was **- - P - - P -**. The strings **SCPTVPS** and **CXPTVPS** are the only two correct strings given these cues. These cues demonstrated that the same letter, in this case "**P**", could occur in different locations in the grammar and that this affects which valid string could be generated. It also showed the participants the concept of the loop by placing the constraint of having to use the looping "**T**" in order to complete the string. Finally, the third and most complex string demonstrated was **- - - T - - - X - -**. In this case, the exemplar **CVCTSSXXVV** was the only correct answer. These cues demonstrated some of the same properties illustrated by the other examples and incorporate the rest of the grammar's properties not yet mentioned. Moreover, it emphasized that strings can take on a rather complex style and length. The rationale for this particular explicit training task was to try and have participants construct a mental representation of the grammar while being exposed to a minimum number of valid strings.

Synchronized Synergistic Training

Participants engaged in the synchronized synergy training task were presented a diagram of the grammar with boxes placed at the transition points (see figure 3). Participants moved from left to right copying each letter of the strings into the corresponding box until the string was completed. Due to the nature of the grammar, more than one letter can occur at the same transition point. For example, the loops in the grammar allow for letters to be repeated, or the switch back toward the end of the grammar that enters an area previously passed. When this occurred the participant was instructed to write the letter to right of the letter(s) already in the box (see figure 3). Participants were shown the proper technique for copying a valid string into their diagram.

The valid string **SCTSSXXVV** was used to demonstrate this task. This string was used for two reasons. First, it was used to illustrate the concept of the loop and the proper way to copy recurring letterings in a transition box. Second, having the double "**X**" followed by the looping letter “**S**” demonstrated the difference between a looping letter and a recurring letter within the grammar. The rationale for this particular synergistic training task was to have participants simultaneously exposed to a set of strings (implicit learning) and the rules that generated them (explicit learning).

Testing Phase

Participants were told that the ship’s computer would display two randomly selected letters from a valid, not-yet-generated, valid string and a series of dashes for each poison food label. The participants were instructed to fill in the dashes with letters that would uncover a poison food label. They worked from left to right in filling in the dashes. When they got to a letter that was already exposed, they had to retype it and continue. After all the dashes were filled in and they reached the end of the string, they pressed enter and the computer went into the data base and matched the string generated by the participant with the closest yet undiscovered valid string.

If the string generated by the participant did not match at least 70% of the characters of the closest valid string, then the program replaced only those characters the participant typed in the correct position (computer-assisted motherese) and the participant was to continue until the 70% criterion was met. However, if the string that the participant typed matched between 70% and 100% of the characters, then the program would go into tracking. The program would go into the tracking mode and retrieve the closest yet unrevealed valid string and display it for the participant to observe, more computer-assisted motherese.

Because valid strings have pairs of letters in common, it was not necessary for the participant to generate the exact string chosen by the computer. Therefore, the participants had some flexibility about which string to generate. However, once a particular valid string was generated, it was removed from the memory bank and could not be generated again in that session. Participants were given 20 minutes to conclude the testing phase. Furthermore, participants were encouraged to attain as many perfect strings (100%) as possible.

While the focus of the study was on generativity (number of valid strings generated in a test session matching 70% of the letters), several additional measures of performance were used to provide a more thorough description of the effects of training methods. These measures were: (a) attempts - the mean number of attempts by each group, (b) generativity - the mean number of valid strings generated with at least a 70% match by each group, (c) accuracy - the mean proportion of attempts that resulted in at least a 70% match by each group, (d) quality - the mean proportion of attempts that resulted in a perfect (100% correct) string by each group.

Results

Only the results for the second test session will be presented here because the two mixed groups (explicit/implicit and implicit/explicit) have not had synergistic training until both weeks were completed. For the interested reader, a table of means for the first sessionand second session for the dependent measurements of generativity and attempts can be found in Appendix C and a similar table of means for quality and accuracy can be found in Appendix D.

The majority of participants in the present study were exposed to a set of valid letter strings. Some researchers (Whittlesea and Dorken, 1993; Vokey and Brooks, 1992) would contend that participants encoded these (22 valid strings repeated 4 times) particular valid letter strings and compared the test strings to the training strings in memory before making a grammatical judgment. Other researchers, (Mathews et al., 1989; Reber, 1989) assert that participants become sensitive to the underlying structure of the grammar and it is this that is used during grammatical judgments. To determine which process took place, the mean proportion of old valid letter strings (valid strings seen during training) generated from each group were compared.

Since the participants in the control group and the purely explicit group never saw any old (training) valid letter strings, these groups served as a baseline. Thus, if none of the groups' mean proportions of generated old letter strings differed from each other, it would seem safe to infer that participants were using more than their knowledge of the set of valid training strings when they made their grammatical judgments.

An ANOVA was run on the mean proportions of old valid letter strings generated by the six groups. The ANOVA revealed a significant effect of training task, *F* (5, 114) = 2.32, *MSE* = .02, *p* = .048. However, a post hoc follow up Tukey HSD test did not show any significant differences between any of the six groups. A Student-Newman Kewls and Bonferroni multiple comparisons did not reveal any significant differences between means either.

In an attempt to discover where the significant effect of training tasks was coming from, another ANOVA was run. This ANOVA tested the mean differences between the proportions of old letter strings generated and the proportions of new valid letter strings generated, Again, the ANOVA revealed a significant effect of training type,
F (5, 114) = 2.77, *MSE* = .02, *p* = .021. A post hoc follow up Tukey HSD test revealed that participants who received purely explicit training generated significantly more old valid letter strings (training strings) than the control group.

This was an interesting finding. Results showed that the only two groups (explicit/explicit and control/control) that did not see any letter strings during training were the only groups to differ significantly in the generation of letter strings. All groups who saw valid letter strings during training did not differ from each other or the explicit/explicit group and the control/control group on this measure. The author concluded that it was safe to say that exposure to valid letter strings during training was not the sole reason for the generation of valid letter strings in this study.

Attempts per Minute

The mean number of attempts per minute participants achieved during the 20-minute test phase was one measure of performance. It was thought to reflect the test strategy adopted by participants because an explicit (reflective) test strategy takes longer (Norman, 1991) than the quicker implicating processing (Reber et al., 1980). Thus, explicitly trained participants make fewer attempts. Table 1 displays each group's mean performance.

An ANOVA revealed a significant effect of training type, F (5, 114) = 14.11, MSE = 4.02, p < .001. A post hoc follow up Tukey HSD test showed that the control/control group (M = 6.86) had significantly more attempts than all other groups. The explicit/explicit group (M = 2.26) and the explicit/implicit group (M = 2.61) did not differ significantly from each other but had significantly fewer attempts than the implicit/explicit group (M = 4.63) and implicit/implicit group (M = 4.93), which did not differ from each other. The synergy/synergy group (M = 3.83) only differed significantly from the control/control group.

Generativity

Generativity was measured as the mean number of valid letter strings generated by each group during the second test session. A string was considered generated when it matched 70% of the letters in a, not-yet-generated, valid string. This was considered to be a measure of participants' ability to generate appropriate (but not necessarily perfect) responses to present environmental cues. Table 1 displays each group's mean performance.

An ANOVA revealed a significant effect of training type, F (5, 114) = 6.81, MSE = 230.84, p < .001. A post hoc follow up Tukey HSD test showed that the implicit/implicit group (M = 45.80), the implicit/explicit group (M = 44.40), and the synergy/synergy group (M = 44.05) generated significantly more valid letter strings than the explicit/explicit group (M = 26.70) and the explicit/implicit group (M = 26.70). The control/control group (M = 38.35) did not differ significantly from any other group.

Accuracy

Accuracy was measured by dividing the number of valid letter strings generated during the second test session by the number of attempts made during that session (i.e. generativity/attempts). This mean proportion was taken as a measure of the accuracy of the test strategy adopted by each group of participants. Table 1 displays each group's mean performance.

An ANOVA revealed a significant effect of training type, F (5, 114) = 10.03, MSE = 466.50, p < .001. A post hoc follow up Tukey HSD test showed that the control/control group (M = 27.54) scored significantly worse on this measure than all other groups. The explicit/explicit group (M = 69.04) scored significantly better than the control/control group and the implicit/implicit group (M = 47.41). There was no significant difference between the implicit/implicit group, the implicit/explicit group (M = 59.64), the explicit/implicit group (M = 61.31), and the synergy/synergy group (M = 64.98).

Quality

The quality of valid letter strings was determined by dividing the mean number of perfectly (100% match) generated letter strings by the mean number of attempts achieved by each group during the second session. This measure was believed to have illustrated which type of training task(s) was better suited for attaining higher quality letter strings. Table 1 displays each group's mean performance.

An ANOVA revealed a significant effect of training type, F (5, 114) = 8.82, MSE = 378.93, $p < .001$. A post hoc follow up Tukey HSD test showed that the explicit/explicit group (M = 34.62) performed significantly better than the control/control group (M = .45), the implicit/implicit group (M = 1.97) and the implicit/explicit group (M = 12.08) which did not differ significantly from each other. The mixed groups implicit/explicit ($M = 12.08$), explicit/implicit ($M = 19.88$), and the synchronized synergy group synergy/synergy ($M = 21.05$) did not differ significantly from each other. Also, groups explicit/explicit, synergy/synergy, and explicit/implicit did not differ significantly.

Table 1. Session Two Means.

Group	Quality	Accuracy	Generativity	Attempts per Minute
CC	.45 (.20)$_{a}$	27.54 (2.65)$_{a}$	38.35 (4.26)$_{ab}$	6.86 (.43) $_{c}$
IE	12.08 (3.70)$_{ab}$	59.64 (4.86)$_{bc}$	44.40 (4.22)$_{b}$	4.63 (.74)$_{b}$
EI	19.88 (4.98)$_{bc}$	61.31 (5.71)$_{bc}$	26.70 (2.64)$_{a}$	2.61 (.36)$_{a}$
II	1.97 (.52)$_{a}$	47.41 (2.90)$_{b}$	45.80 (2.63)$_{b}$	4.93 (.26)$_{b}$
EE	34.62 (6.76)$_{c}$	69.64 (6.27)$_{c}$	26.70 (3.15)$_{a}$	2.26 (.35)$_{a}$
SS	21.05 (5.40)$_{bc}$	64.98 (5.38)$_{bc}$	44.05 (3.08)$_{b}$	3.83 (.39)$_{ab}$

Note: Means occupying the same column and having different subscripts are significantly different at $p < .05$ on the Tukey HSD post hoc test of comparisons.

Standard errors are in parentheses

Discussion

The purpose of this study was to investigate if implicit learning processes alone could support generativity and to look for possible interactions between implicit and explicit learning. The training tasks were designed to evoke one learning mode while attempting to eliminate the contamination of the other learning mode. The synchronized synergy training task was also employed in this study in an attempt to activate both learning modes simultaneously. Even though one of the main goals of this study was to investigate generativity, we also looked at measures of attempts, measures of accuracy, and measures of quality. If these extra measures would not have been calculated, we would have received a false impression of the type of training best suited for a particular task.

The best type of training method depended upon which measurement was taken into account. Participants were told that if they generated a string with a 70% match, they would be allowed to proceed to the next string. However, they were also encouraged to generate perfect (100% match) strings. Thus, they were working for both speed (finding as many strings as possible) and accuracy (generating a 100% match string).

Casual observation of the participants performing the cued generate test suggested that explicitly trained participants were using a very different strategy as compared to the implicitly trained participants. Many participants who had received purely explicit training were observed by the author drawing in the air with their finger. One could interpret this strategy as a conscious attempt to reconstruct the grammar. Some of the other participants in this group would look up in what appeared to be conscious reflection. Most participants would engage in these strategies before typing a letter or two, and then perform one of these strategies again before proceeding to type more letters. In contrast, most participants who received purely implicit training would rarely look away from the computer screen. Many times participants in this group would type some letters, look at them on the screen, press the backspace key, and retype letters before pressing the enter key.

During post experiment questioning, the majority of participants who had purely explicit training stated to the author that they were, in fact, attempting to reconstruct an image of the grammar. Moreover, the majority of participants who received purely implicit training stated to the author that they pressed the backspace key often because they felt “something didn’t seem right in the string”.

As for participants in the mixed training groups, they seemed to revert back to their week one strategy within minutes of the second week’s cued generate test. The majority of participants in the mixed training conditions stated to the author during post experiment questioning that they felt “more comfortable” with the training method they learned first. Participants who received the synchronized synergy training seemed to vacillate between the implicit group’s strategies and the explicit group’s strategies. The control group was observed performing what Miller (1969) called mindless or “cyclic strategies”. These strategies consisted of selecting one letter at a time and filling in all the dashes before pressing the enter key. They continued this process until a string possessing a 70% letter match to a not yet discovered valid letter string was generated. Again, the majority of participants who received synchronized synergy training and participants in the control group confirmed, during post experiment questioning, the author’s observations of their strategies

The performance data seemed to have supported these observed test strategies. Looking at the measure of attempts, the control group made significantly more attempts than all other groups. Given that an attempt was counted every time the enter key was pressed, the “mindless/cyclic” strategies adopted by the control group would seem to take less time per attempt. Thus, the control group achieved significantly more attempts during the 20-minute test phase than any of the other groups.

Participants who received purely implicit training or received implicit training during their first session implicit/explicit, performed significantly more attempts than the participants who received purely explicit training or explicit training during their first session, explicit/implicit. Reber et al. (1980) reported that participants who received implicit training had significantly faster reaction times than their counterparts in the explicit conditions. Norman (1991) asserted that someone engaged in reflective (explicit) thought takes a longer more deliberate approach to processing stimuli than someone engaged in experiential (implicit) processing of stimuli. Thus, both Reber et al.’s and Norman’s accounts support the patterns of performance data and the self report strategy descriptions provided by the participants.

The participants who engaged in synchronized synergy training did not differ significantly in number of attempts from the participants in implicit, explicit, or mixed training conditions. It seems that their “slower” explicit (reflective) mode was somehow combined with their “quicker” implicit (experiential) mode. This pattern of results suggests that synchronized synergy training was capable of evoking both learning modes.

The measure of most interest in this study was generativity. As mentioned above, generativity was measured by the total number of valid letter strings generated in the 20-minute cued-generated test. It seems that the speed of the implicit mode was most beneficial to generating letter strings. The participants who had purely implicit training generated significantly more valid letter strings than the participants who received purely explicit training. They also generated significantly more valid letter strings than the participants who received explicit training during their first week explicit/implicit. This provided evidence suggesting that implicit learning processes alone can support generativity. Also, participants who received implicit training during their first session implicit/explicit generated significantly more valid letter strings than participants who received purely explicit training or explicit training during their first session explicit/implicit. This pattern of results is what Reber et al. and Norman would have predicted based on the speed of implicit processing. Finally, participants who received synchronized synergy training produced the same pattern of results as the participants who received purely implicit training and the participants who received implicit training during their first session implicit/explicit. Thus, when it came to generativity, the “quicker” implicit processes in the purely implicit, synchronized synergy, and implicit/explicit groups facilitated the participants in generating more valid letter strings within the 20 minute test phase.

When the measure of accuracy was examined, a different view of the effects of different training types emerged. Accuracy was defined as the proportion of attempts that resulted in a valid letter string being generated (i.e. generativity/attempts). Participants who received purely explicit training were significantly more accurate in generating valid strings than the participants who received purely implicit training. However, participants who received purely implicit training did not differ significantly from the other four experimental groups. This finding suggested that even though purely implicit training alone supported generativity, it was significantly less accurate than purely explicit training. However, participants who received synchronized synergy training were equal in accuracy to the most accurate group explicit/explicit. Thus, the synergistic effect observed in the synergy/synergy group when generativity was measured also appeared when the measure of accuracy was examined.

Finally, the measure of quality was examined. Again, quality was determined by the mean proportion of each group's attempts that resulted in a perfect (100% letter match) letter string. Participants who received purely explicit training had a quality measurement significantly higher than participants who received the purely implicit training and participants who received implicit training during their first session implicit/explicit. Moreover, participants who received explicit training during their first session explicit/implicit significantly out performed participants who received the purely implicit training. Participants trained using the synchronized synergy training task were not significantly different than participants in the purely explicit group who generated the highest quality strings. Thus, the synergistic effect observed in the synchronized synergy group on the measures of generativity, and accuracy was also present when the quality measurement was examined.

Looking at the over pattern of results, Norman's (1991) assertion that reflective (explicit) processes are slower and more deliberate than experiential (implicit) processes is supported by the data of the present study. The significantly fewer attempts achieved by the purely explicit group and the explicit/implicit group would seem to imply that explicit processes were activated during the second cued generate test. Since the participants in the purely explicit group were engaged in slower processes, this strategy led them to achieve significantly fewer attempts. Thus, they generated significantly less valid letter strings than the purely implicit group and the implicit/explicit group.

The purely explicit group and the explicit/implicit group engaged in more deliberate (Norman, 1991) processing, but the data revealed that their deliberateness was well utilized. Even though they had significantly fewer attempts than the purely implicit group and the implicit/explicit group, their attempts were significantly more accurate in the generation of valid letter strings. Moreover, the slower and deliberate explicit processing facilitated the participants in the generation of significantly more perfect (100% letter match) strings. Thus, the purely explicit group and the explicit/implicit group seemed to have suffered when it came to speed (i.e. number of attempts and generativity), but they benefited greatly from the slow deliberate processes when it came to precision.

As mentioned previously, Reber et al, (1980) reported that participants who received implicit training produced faster reaction times during the test phase. As a result of this finding, they asserted that implicit processing is quicker than explicit processing. The data from the present study seem to back up their contention. Participants, who received purely implicit training and implicit training during the first session implicit/explicit, achieved significantly more attempts than participants who received purely explicit training or explicit training during their first session explicit/implicit. As a result of achieving significantly more attempts, these participants generated significantly more valid letter strings (i.e. generativity).

Unfortunately, the speed of the implicit processes used to achieve these significant measures had an adverse effect on the groups' precision. The participants who received purely implicit training were significantly less accurate than the participants who received purely explicit training. When it came to the quality of the letter strings generated, participants who received purely implicit training performed significantly worse than participants who received purely explicit training, explicit training during their first session explicit/implicit, and synchronized synergy training. Thus, the speed of implicit processing comes at the expense of precision.

On the other hand, explicit processing is slow but results in better precision. A method needed to be developed that would integrate both learning modes into one task to produce the optimal benefits of each mode alone (i.e. synergistic effect) (Roussel, 1998). This was the premise that led to the development of the synchronized synergy training task.

The data provide evidence that the synchronized synergy training task produced its intended effect. Participants who received the synchronized synergy training did not perform significantly less well than the best group on any of the measures except for significantly less attempts compared to the control group. Although, the control groups' mindless/cyclic strategy was fast it was very ineffective in terms of quality and accuracy.

Participants who received synchronized synergy training generated significantly more valid letter strings than participants who received purely explicit training and those who received explicit training during their first session explicit/implicit. Also, participants trained using the synchronized training task generated significantly better quality letter strings than participants trained with the purely implicit training task.

Finally, the participants who received synchronized synergy training performed just as well as the best performance of quality explicit/explicit group and the most accurate explicit/explicit group. Thus, participants who received synchronized synergy training produced a better effect on generativity of letter strings, accuracy by which the letter strings were generated, and the quality of the generated letter strings than either the purely implicit task or the purely explicit task.

As far as which training method would be the best to implement, these results suggest that it depends on the demands of the task. If practically possible, the synchronized synergy training should be used since it produces the best qualities of both learning modes. Unfortunately, in many real life situations (e.g. natural language, arithmetic), it is not obvious how one would implement synchronized synergy training.

If synchronized synergy training is not possible, one should consider the requirements that need to be met in a given situation. If accuracy or precision is of utmost importance, then explicit training would be preferred. For example, if one is an engineering student, then the properties of physics and ability to calculate stress endurance of certain materials should be taught through the explicit mode. On the other hand, if ability to generate quickly is more important than accuracy of the production, then the implicit learning mode should be optimal. For example, an anti-aircraft gunner needs speed and numerous hits rather than accuracy. In other words, number of hits in this situation is more effective in accomplishing the task than a more deliberate process.

At this point the reader is reminded that measuring generativity of implicit knowledge has just recently been implemented (Mathews & Cochran, 1997; Mathews et al., 2000). Moreover, as stated in the introduction, the discrimination test has been the most commonly used measurement of implicit knowledge acquisition (Dienes, Broadbent, & Berry, 1991; Gomez & Schvanevedlt, 1994; Knowlton & Squire, 1994; Manza & Reber, 1997; Mathews et al., 1989; Perruchet & Gallego, 1997). Thus, in the formulation of implicit learning theories, the researchers were focused on discrimination data in determining what results should occur. Consequently, these theories must be extrapolated to predict outcomes derived from a generativity measure. As a result, the author will attempt to predict the expected outcomes for each theory. Moreover, he will also try to explain why these results on generativity and interactions would be expected.

Lewicki (1986) proposed the internal processing algorithm (IPA) theory of implicit knowledge acquisition. He asserts that an IPA is totally non-conscious and once developed could never be consciously accessed or modified. Lewicki's theory would seem to suggest that the purely implicit group would have had the best chance at developing an IPA because they were exposed to more repetitions of valid letter strings than any of the other groups. If an IPA were developed during the observation of the set of valid letter strings, it seems that Lewicki's IPA theory would predict generativity. Moreover, since the set of letter strings used for training was representative of the whole grammar, it may be safe to say that if an IPA did develop, the strings would be generated in an accurate manner and be of high quality.

Thus, Lewicki's IPA theory would have correctly predicted that the purely implicit group would have performed the best on the generativity measure. Unfortunately, it seems that the theory would have fallen short when looking at the accuracy measure and the measure of quality because these measures were relativity low in the implicit group. As for interactions between the implicit and explicit learning modes, the IPA theory does not predict any. Lewicki (1986) leaves no room in his IPA theory for interactions between the two learning modes by saying "The fact that the IPA is non-conscious in all aspects of its acquisition and subsequent operation ...” (p 32). The IPA theory was not supported on its assertion that there are no interactions between the two learning modes. The synchronized synergy group performed significantly better than the explicit/explicit group on generativity, significantly better than the implicit/implicit group on quality, and equal to the best performing group explicit/explicit on accuracy. Thus, not only do interactions occur between the two learning modes but some of these interactions produce synergistic effects.

Abstraction theory proposes that implicit knowledge is acquired through the induction of the rules that govern a structured domain (Reber, 1989). The induction of these rules is believed to be done without conscious reflection. A mental representation of a domain’s rule system is said to be developed from specific instances (Manza & Reber, 1997) and partial memories of letter strings (Mathews, 1991). From this mental representation, abstract rules (e.g. partial memories, spatial location) can be manipulated and recombined.

The manipulation and recombination of abstract rules is said to be able to produce novel letter strings (Mathews & Roussel, 1997) which is the essence of what Corballis (1991) meant by generativity. Researchers who support the abstraction theory (Mathews et al., 1989; Reber et al., 1980) contend that the any combination of implicit and explicit learning is better than either alone. This synergy produces more powerful responses (Sun, 1995). Moreover, if the two learning modes could be integrated into one training task, the optimal benefits of each measure could be produced (Roussel, 1998) thus providing and more powerful training method (Sun, 1995).

This integration of the two learning modes is what the synchronized synergy synergy/synergy training task provided. Synchronized synergy training provides the speed of implicit processing (Reber et al., 1980) and the accuracy of explicit processing (Norman, 1991). Hence, the abstraction theory would have predicted that the speed of implicit processing would have provided the power to generate more valid letter strings than the purely explicit group. In addition, the accuracy of explicit processing would have provided the power to produce better quality strings than the purely explicit group (Sun, 1995). This is exactly what happened.

The synergy/synergy group generated significantly more valid letter strings than the purely explicit group and equal to the best performing group (purely implicit). Moreover, the synergy/synergy group generated letter strings of significantly higher quality than the purely implicit group and equal to the highest quality group (purely explicit). Also, the integration of implicit processing and explicit processing enabled the synergy/synergy group to perform just as accurate as the purely explicit group who had the highest accuracy score. Consequently, synchronized synergy training provided participants with the knowledge that allowed them to perform equal to the highest performing group on all measures in the present study.

The exemplar theory asserts that whole letter strings are encoded and stored in memory. When a string is encountered during test, it is compared to the valid strings in memory and deemed grammatical or ungrammatical (Vokey & Brooks, 1992). The purely implicit group and synchronized synergy group saw 22 valid letter strings repeated four times during each of two training sessions. The explicit/implicit group also saw the set of 22 valid letter strings repeated four times but only during the second session. This is of importance because this is the session data that the present study has analyzed and used to draw its conclusions.

Exemplar theory says that these are the only valid letter strings that participants should have encoded and stored in memory. Following this line of reasoning, participants in the implicit/implicit group, synergy/synergy group, and explicit/implicit group should have been predicted to perform very poorly on the generativity measure since they were supposedly only able to generate the 22 strings stored in memory. On the other hand, the participants in the three groups just mentioned should have been predicted to perform fairly well on the quality of the letter strings that they did generate. The implicit/explicit and explicit/explicit groups should have been predicted to perform worst of all. Unfortunately, there is an inherent problem for the exemplar theory when the cued generate test is being used to measure generativity.

The computer presents the participants with a letter string represented by dashes and two randomly chosen letters in their grammatically correct positions within the string. There are 177 possible letter strings in this study that could appear on the screen. However, the participants only have 22 strings in memory. This would not be a factor in a discrimination test because participants would determine grammaticality based on how similar the test string was to the strings in their memory bank (Vokey & Brooks, 1992). Conversely, the cued generate test provides only two letters of a valid letter string and the participant would need to have a valid string in memory that fit that particular template to be able to generate the rest of the string. This would have seemed to be a very inaccurate way to generate valid letter strings.

The significantly high levels of generativity for the implicit/implicit group and the synergy/synergy group are counter to what the exemplar theory should have predicted. The explicit/implicit group performed significantly worse than the two previous groups but still above the 22 strings they should have stored in memory. Also, the quality measure of the implicit/implicit group was worse than all other groups except for the control group. The quality measure of the synergy/synergy group and the explicit/implicit group was equal to the highest performing explicit/explicit group. The accuracy measures that the exemplar theory should have predicted as poor were no different than any other group except the control group.

All of the exemplar theory's predictions should have been predicated on the participants' strategy of matching a test string template with the 22 stored strings and generating one of the strings in memory. However, when the number of old strings (seen before and, therefore, most likely to be generated) were examined, a very revealing pattern was uncovered. The synergy/synergy group and the explicit/implicit group that were correctly predicted to generate high quality strings only generated an average of 4.65 old valid letter strings and 2.9 old valid letter strings respectively. The implicit/implicit group generated an average of 3.75 old valid letter strings. As a result of these low performance measures on the strings that should have been generated according to the exemplar theory, it seems safe to say that something more than encoded instances was responsible for the performances of the groups.

Chunking theory of implicit knowledge acquisition contends that upon encountering a stimulus in the environment, one parses it into smaller units called chunks (Perruchet & Gallego, 1997; Servan-Schreiber & Anderson, 1990). Stimuli are said to be parsed into the smallest number of chunks possible and stored as traces in long term memory. When one encounters a stimulus, the memory traces (chunks) are call up to match the stimulus. The more a chunk is retrieved then the more strength it gains and the more likely it will be called up again (Servan-Schreiber & Anderson, 1990). Moreover, a chunk retrieved can also be elaborated on and create a new chunk. The theory was formulated for perception and retrieval processes like those used in the discrimination test of artificial grammar studies. It gets more complicated when it is used in a generativity test.

Servan-Schreiber and Anderson (1990) used a computer simulation on the experimental results obtained during Miller's initial 1958 study into generativity. With generativity "… it was necessary to transform the outcome of the perception process … into an act of recall" (p 600) (Servan-Schreiber & Anderson, 1990). They worked from the assumption that a string could be recalled only if it were "maximally familiar". Maximal familiarity was reached at the "word" level (maximum of three letters) unless they encoded runs of a letter (the same letter repeatedly). Then a word could be longer than three letters. Also revealed was that a redundant letter set generated from a structured domain was easier to encode. The implicit/implicit group and the synergy/synergy group provided a redundant structured letter set.

Since chunking theory was formulated on the perception and identification of chunks rather than the generation of chunks, makes its predictions difficult to determine. Maximal familiarity at the word level is the key component. If maximally familiarity occurs with a word that contains one letter (as the cues in the cued generate test unless the two cues are side by side), then generativity would seem to be high. In this case, the implicit/implicit group and the synergy/synergy group should have been predicted to perform best on generativity and quality which is what happened with the present data. On the other hand, if maximal familiarity at word level needed more than one letter to retrieve and activate a chunk, then generativity and quality would have been low and counter to the present data. In short, it is difficult to determine what the chunking theory would predict without knowing which words (one to three letters) gained more strength, thus retrieved and used more.

The interactions between implicit and explicit processes do occur in chunking theory. The process of parsing a stimulus into chunks is said to be nonconscious (Perruchet & Gallego, 1997; Servan-Schreiber & Anderson, 1990). However, the process by which the chunking took place during encoding can be understood through explicit thought processes (Servan-Schreiber & Anderson, 1990). On the other hand, Perruchet and Gallego (1997) assert that consciousness, hence explicit knowledge, is not required for “behavioral adaptation” to a structured domain. Thus, Servan-Schreiber & Anderson (1990) would say that both modes are involved but that implicit processes are active during encoding but that explicit processes could be activated during retrieval. However, Perruchet and Gallego (1997) posit that consciousness (explicit knowledge) in not needed to exhibit implicitly acquired knowledge. These theories may need to be modified to explain these measures of generativity.

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Appendix A

The Poison Food Game Cover Story for Training Phase

All food on board a military transport vessel in space was destroyed. A missile hit a storage bay during an attempt to rescue a civilian colony. We managed to save 136 civilian survivors of the colony: however, all passengers and crew of a colonial vessel were found dead. The cause of death was the result of an epidemic of invisible space slime that was introduced by alien invaders. Since we need extra food for the long voyage home, military crew loaded on board a large quantity of food salvaged from the colonial vessel.

Before loading the food on board our ship, the shipment of food was treated with a new gas that effectively kills remaining slime on the cans of food. There is no danger of an epidemic of slime contamination on our ship. Unfortunately, any slime that penetrated the cans of food produced a deadly poison that cannot be tasted or removed. Therefore, consumption of the food results in serious illness and eventually death.

Although records of the colonial vessel were destroyed, we know something about the ship from communication between the vessel and the space colonists. The food came in many different varieties in order to mimic the varieties of food available on earth. A robotic food delivery system was used to distribute cans of food to each location using a computerized system. Consequently, cans of food were often shuffled around to several locations on the ship before being consumed or returned to one of three main storage depots.

Once the epidemic of slime poisoning occurred, new food inspection and decontamination procedures were implemented. Measures were taken to decontaminate all cans of food on a routine basis. Food inspectors were posted at several locations around the ship. Their job was to monitor the food passing through the control point and stamp an assigned letter to the next available space on a label when it passed through the control point.

Inspectors periodically worked in teams so that a letter does NOT necessarily identify the individual inspector, but identifies the assigned team. However, different teams of inspectors manned the control points on different days; consequently, the letter sequences on the cans do NOT directly tell us which control points food passed through. Fortunately, any contaminated can of food that passed through at least one properly functioning decontamination device would be safe to eat.

Our lab can determine if injecting the can of food with a radioactive tracer poisoned individual cans of food. Geiger counter readings of 10 or greater following injection of the radioactive tracer indicate that the food is poisoned. Any reading below 10 (9 or less) is perfectly safe to eat. The test can only be conducted on whole cans of food and tested food cannot be consumed. Even if it turns out that a tested can was not contaminated by space slime, it still cannot be eaten after testing since the test itself renders food into a deadly poison.

Therefore, we have a dilemma in that we must use this salvaged supply of food for the trip home. Yet, we know that about 20% of the cans of food contain a deadly poison. We can test cans of food to see if they are poisoned, but tested food cannot be consumed. We must find a way to identify safe cans without using the radioactive tracer so we can feed our people during the long flight home.

Your mission is to learn the “poison paths” that a can of food could have passed [explicit training instructions].

Your mission is to bubble-in the few poison food labels saved since this method has been shown to help identify similar strings [implicit training instructions].

Your mission is to trace the few poison food labels recovered through a diagram of the “poison paths” recovered [synergistic training instructions].

Appendix B

The Poison Food Game Instructions for the Test Phase

Using your knowledge of the "poison paths", the captain has asked that you make a list of all the possible routes that the food could have traveled so that we can discard all the cans of poison food with those labels [explicit training instructions].

You have just experienced a small sample of poison food labels. With the knowledge you gained, the captain has asked that you make a list of other poison food labels. We know from the records recovered that there are many more and they must be discarded [implicit training].

You have just been exposed to a small sample of poison food labels and the paths that they have taken. The captain has asked that you make a list of other poison food labels. We know from the records recovered that there are many more and they must be discarded [synergistic training].

To help you in your task, the computer will display partial can labels of potentially poisoned food. The UNKNOWN letters of the can label will be replaced by DASHES. You should try to make a complete label by filling in the missing letters.

For example, if the computer displays - - T - - S, then you might type CTTVVS.

After you type in your can label, the computer will give you a Geiger counter reading which tells you the level of radioactivity on the can with that label.A reading of 10 indicates maximum contamination and means that you have found one of the cans that DID NOT pass through a working decontamination device. In other words, it only passed through poison paths and contains poisoned food. Readings of less than 10 indicates lower levels of contamination in cans that passed through at least one working decontamination device. Please note that these cans are NOT poisoned. If you get a reading of less than 7, the computer will give you more CLUES and you can try again. When you locate a can with a Geiger counter reading of 7 or greater, the computer will automatically scan all nearby cans, find the source of contamination (the can with a reading of 10) and display its label on the screen for you.

When the computer tells you that it is "tracking…", it means that you are close to a can with a reading of 10 and the computer is looking for that can. When it finds that can, the label will be displayed on the screen. Once a poison can has been found, that particular can is discarded. So if you type in that label a second time, you will not get a reading of 10.

Try NOT to type in the same label twice.

Your GOAL is to find all poisoned cans (10s) aboard the ship.

To BEGIN, please press "3" on the computer.

Appendix C

Session Means for Generativity and Attempts

	Generativity	Generativity	Attempts per Minute	Attempts per Minute
Group	Session 1	Session 2	Session 1	Session 2
CC	25.40 (2.73)$_b$	38.35 (4.26)$_{ab}$	5.20 (.31)$_c$	6.86 (.43)$_c$
IE	38.60 (2.45)$_c$	44.40 (4.22)$_b$	5.33 (.43)$_c$	4.63 (.74)$_b$
EI	15.50 (2.22)$_a$	26.70 (2.64)$_a$	1.33 (.14)$_a$	2.61 (.36)$_a$
II	34.25 (2.46)$_{bc}$	45.80 (2.63)$_b$	4.37 (.27)$_c$	4.93 (.26)$_b$
EE	15.40 (2.01)$_a$	26.70 (3.15)$_a$	1.58 (.33)$_a$	2.26 (.35)$_a$
SS	27.05 (2.34)$_b$	44.05 (3.08)$_b$	3.04 (.35)$_b$	3.83 (.39)$_{ab}$

Note: Means occupying the same column and having different subscripts are significantly different at $p < .05$ on the Tukey HSD post hoc test of comparisons.

Standard errors are in parentheses

Appendix D

Session Means for Quality and Accuracy

Group	Quality Session 1	Quality Session 2	Accuracy Session 1	Accuracy Session 2
CC	.05 (.17)$_a$	.17 (.20)$_a$	23.86 (1.75)$_a$	27.54 (2.65)$_a$
IE	.92 (.37)$_a$	11.07 (3.70)$_{ab}$	38.60 (2.53)$_{ab}$	59.64 (4.86)$_{bc}$
EI	27.11 (6.05)$_b$	19.01 (4.99)$_{bc}$	15.50 (7.17)$_c$	61.31 (5.71)$_{bc}$
II	.70 (.40)$_a$	1.45 (.52)$_a$	34.25 (2.71)$_{ab}$	47.41 (2.90)$_b$
EE	25.46 (6.35)$_b$	32.68 (6.76)$_c$	15.40 (6.38)$_c$	69.64 (6.27)$_c$
SS	5.47 (1.62)$_a$	19.30 (5.40)$_{bc}$	27.05 (4.33)$_{bc}$	64.98 5.38)$_{bc}$

Note: Means occupying the same column and having different subscripts are significantly different at $p < .05$ on the Tukey HSD post hoc test of comparisons.

Standard errors are in parentheses

Vita

Thomas James Domangue was born in Chauvin, Louisiana, on August 4, 1961. He is the first born to Elgin Domangue and Glenda W. Domangue. In 1979 he graduated from South Terrebonne High School. During the summer of 1979, he was left paralyzed from the chest down in an automobile accident. He received his bachelor's of arts degree in psychology and a minor in criminal justice from Nicholls State University during the 1998 fall commencement. He was accepted to the doctoral program in cognitive psychology at Louisiana State University in the fall of 1999. Thomas is a candidate for the master of arts degree in psychology for the 2002 fall commencement at Louisiana State University. Thomas plans to continue his pursuit of a doctorate in cognitive psychology and a minor in industrial/organizational psychology at Louisiana State University.