Training and measuring word recognition skills

from an automaticity perspective

Johanne P. Courte

A Thesis

in

The Department

of

Psychology

Presented in Partial Fulfillment of the Requirements
for the Degree of Master of Arts at
Concordia University
Montréal, Québec, Canada

April 1992

ISBN 0-315-80953-1

Abstract

Training and measuring word recognition skills from an automaticity perspective

Johanne P. Courte

The purpose of the present study was to investigate processing changes in word recognition following training. Of particular interest was whether consistent practice would facilitate word recognition by speeding its processing stages. A consistent mapping category search task was used to train processes involved in word recognition. In addition, a lexical decision task was implemented to evaluate automaticity in word recognition prior to and after training. It was expected that word recognition in the category search task would improve as evidenced by shorter response latencies and a reduction in reaction time variance as a function of training. Also increased automatic net effects were anticipated as measured by the primed lexical decision task in support of a continuum view of automaticity. A significant reduction in mean reaction time and reaction time variance was found in the category search task for trained items between sessions 2 and 13 in a 31 session training process. However, the hypothesized effects of training on word recognition were not supported. No significant difference between pre- and post-training automatic effects were observed. The discussion integrates a new direction in the research on mechanisms involved in the development of automaticity. New methods for evaluating automatic and

controlled processes within a task are considered in view of the present findings.

Acknowledgements

I wish to thank my thesis supervisor, Dr. Norman Segalowitz, for his guidance on completing this research and for his helpful and constructive comments during the writing of this thesis.

I also wish to extend my appreciation to committee members, Dr. Mel Komoda and Dr. Jacinthe Baribeau, for taking the time to review and to offer insightful comments on an earlier draft of this thesis.

Finally, many thanks to my family and to Dale for their patience and unconditional support throughout the years.

Table of Contents

	Page
List of Figures	viii
List of Appendices	ix
List of Tables	x
INTRODUCTION	1
Models of Reading	3
Training Automaticity	6
Purpose of the Study	12
Category Search Training	12
Learning Mechanisms	19
Primed Lexical Decision Task	23
Semantic Priming Mechanisms	33
Neutral Prime	37
Questions addressed	40
METHOD	43
Subjects	43
Materials and General Procedure	43
Screening Procedure	44
Testing Stimuli	45
Memory Task	46
Lexical Decision Task	47

Training Procedure _ 52

RESULTS _ 56

DISCUSSION _ 83

REFERENCES _ 95

APPENDIX A _ 102

APPENDIX B _ 104

APPENDIX C _ 106

APPENDIX D _ 109

APPENDIX E _ 113

APPENDIX F _ 116

APPENDIX G _ 121

List of Figures

	Page
Figure 1. Example of a primed lexical decision task trial	51
Figure 2. Example of a consistent mapping trial	55
Figure 3. Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task	59
Figure 4. Standard deviation (ms) per session as a function of training for surprise and trained items in the category search task	60
Figure 5. Percentage of correct responses as a function of training for surprise and trained items in the category search task	61
Figure 6. Mean reaction time (ms) and standard errors as a function of blocks of 5 sessions for trained and surprise items in the category search task	64
Figure 7. Mean reaction time (ms) and standard errors as a function of training level in the lexical decision task	76

List of Appendices

	Page
Appendix A. List of targets	102
Appendix B. Memory Task Stimuli	104
Appendix C. Lexical Decision Task Stimuli	106
Appendix D. Training Stimuli	109
Appendix E. Training Targets	113
Appendix F. Tables of Automatic and Controlled Processing Net Effects	116
Appendix G. Training Figures	121

List of Tables

Page

Table 1. Relatedness and Expectancy Conditions in a Primed Lexical Decision Paradigm ___________ 27

Table 2. Predicted Effects of Automatic and Controlled Processing by SOA, Expectancy, and Relatedness ________________________ 31

Table 3. Calculating Automatic and Controlled Processing Net Effects without a Neutral Prime __________ 39

Table 4. Testing Blocks in the Primed Lexical Decision Task ______________________________ 49

Table 5. Automatic and Controlled Processing Net Effects (in ms) for Trained and Untrained Items for $\underline{N} = 8$ resulting from the Burke *et al.* (1987) formula ___________________________ 69

Training and measuring word recognition skills from an automaticity perspective

Reading is very much a part of our everyday life. It is a tool that we can hardly live without. As adult readers we take for granted the fact that we can perform such a complex task quite effortlessly. This overt lack of effort in our ability to read is simply one feature of the complex skill of reading that we have acquired over many years. Other characteristics of skilled reading include speed and greater text comprehension. Typically the skilled individual reads faster and/or has better comprehension than a less skilled reader (Perfetti, 1985). When learning to read, the unskilled individual might be overwhelmed by the information and consequently, processing or assimilation of this information is laborious. With practice however, the beginner will overcome certain information processing difficulties and acquire the ability to read fluently. Although improvement in task performance is expected to occur with practice, Frederiksen, Warren, and Rosebery (1985a; 1985b) have demonstrated that training individual components of a complex skill, specifically reading, can lead to better general improvement (also, Crossman, 1959; LaBerge & Samuels, 1974). This thesis will investigate practice effects on a specific component of reading skill.

Within the framework of reading a text, time is spent in processing information at different structural levels and these levels are somehow interconnected (through top-down, bottom-up, or interactive processing; Stanovich, 1980). For example, the reader must make use of the printed information to identify words (e.g., decoding the letter string), select from long-term memory the appropriate meaning of these words, integrate the meanings into working memory, then apply his or her prior knowledge to form or modify an on-going mental model (schema) of the text for the purpose of comprehension (Perfetti, 1985). In an attempt to identify the features that distinguish skilled from less skilled readers researchers have grouped these components into separate levels according to their cognitive processing demands. Lexical access (the extraction of a word's meaning from its visual features; Stanovich, 1991), syntactic and propositional encoding are components that require low level processing. Components that help build a meaningful text model or schema require higher level processing. Comprehension in skilled reading requires the proper coordination of these components. Reading ability differences can arise from within either of these two processing levels (Graesser, Hoffman, & Clark, 1980; Perfetti, 1985). Graesser *et al.* (1980) examined the distribution of processing times to different structural components of reading. Graesser collected reading times as a measure of resource allocation to sentences in text passages. The macrostructure components, which require higher level processing, consisted of the number of new argument nouns, passage familiarity and narrativity. The microstructure components, which require low level processing, consisted of the average time required to process a word including semantic activation, syntactic and propositional analyses. The results from the first experiment revealed that macrostructure components required most of the reading time compared to the microstructure components. However, differences between slow and fast readers were found in processing times of microstructure components: slower readers took more time to perform lexical, syntactic, and propositional analyses within sentences. Perfetti's (1985) research also revealed that individual differences were located in the processing of microstructure components. For example, he found that skilled readers were more accurate and faster than less skilled readers in lexical access and naming tasks. In addition, skilled readers were faster in tasks that required lexical look-up, i.e., identifying a string of letters as a word or nonword. Although more attentional resources are required for the processing of macrostructure components than microstructure components regardless of reading ability, less skilled readers are slower at processing lower level components than skilled readers.

Models of Reading

Perfetti's (1985) verbal efficiency theory states that individual differences in reading skill arise from differences in the efficiency of processing lower level components. Also, LaBerge and Samuels (1974) have suggested that lower level reading components must become automatic before higher level ones can develop fluency. These models are based on the assumption that we have a limited-capacity pool of attentional resources (Kahneman, 1973) and that the efficient allocation of these resources is fundamental for comprehension. If each component involved in the complex skill of reading required attentional resources then performance would be greatly limited if not impossible because resource capacity would be exceeded by the competing demands of each component. If, on the other hand, very little attentional resources were required for processing lower level components then resources would be available to be used more efficiently in the processing of other reading components such as the integration of propositions and general text comprehension. It is believed that some reading components have become overlearned after years of reading experience. For example, it is assumed that skilled readers are faster at lexical access because this component has become overlearned or automatic, i.e. capacity-free. Consequently, for the skilled reader the word recognition component can operate in parallel to the text integration component because they are not competing for resources. In other words, skilled readers can direct their attentional resources more effectively because some components are being processed automatically while others are being processed concurrently. If lexical access has not become automatic it will compete for attentional resources and reading speed will be slowed because components requiring attention cannot operate simultaneously. Therefore it would seem that automatic processing in the word recognition component is a critical if not an essential attribute for successful reading performance and this can be achieved through practice.

Stanovich (1991) has recently introduced an alternative to the limited-capacity approach to understanding reading ability differences. This approach, referred to as 'acquired modularity' of the word recognition module, emphasizes that differences between skilled and less skilled readers can be traced to the word recognition level in reading. In contrast to the above mentioned theories, the word recognition component is seen as a module that becomes independent of the reader's background knowledge, as reading skill develops. Thus, as skill is acquired in recognizing words, this component becomes modular in that it relies less on other sources of information (such as context) for recognition. The acquisition of modularity means that a component, such as word recognition, would become functionally autonomous, i.e., independent of other informational structures. The idea of modularity is very different from acquired automaticity in that efficiency in word recognition is not seen as a reduction in resource demands (or an increase in resource availability) but as an acquired independence from other structures. Although Stanovich's theory is attractive because it does not involve the notion of limited cognitive resources, no methods have been suggested for training componential 'modularity'. There is, however, a method for training automaticity and this is what will be addressed in the following section.

Training Automaticity

There is a general consensus among researchers that practice leads to changes in task performance, i.e. improvement. Such changes are measured as faster reaction times (RTs), improved response accuracy, a reduction in task interference when two tasks are performed concurrently, an increase in task interference such as in a Stroop-related task, and even changes in evoked-related potentials (Crossman, 1959; Fisk & Schneider, 1983; Frederiksen *et al.*, 1985a; 1985b; Hirst, Spelke, Reaves, Caharack, & Neisser, 1980; Logan, 1985a; Newell & Rosenbloom, 1981; Rabbitt & Banerji, 1989; Schneider & Fisk, 1984; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977; Strayer & Kramer, 1990). These performance characteristics are commonly associated with the concept of automaticity in that practice has somehow transformed the cognitive processes involved in the task from controlled to automatic. These two forms of processing are qualitatively and quantitatively different from each other. On the one hand automatic processing is characterized as being fast (Neely, 1977; Posner & Snyder, 1975), effortless (Schneider & Shiffrin, 1977), undemanding of attentional resources (Hasher & Zacks, 1979; LaBerge, 1981; Schneider & Shiffrin, 1977), obligatory, i.e., unable to stop processing once it has begun (Logan, 1985a), and autonomous, i.e. stimuli elicit processing in the absence of intention (Logan, 1980; Posner & Snyder, 1975; Shiffrin & Schneider, 1977; Zbrodoff & Logan, 1986). In contrast, controlled processing is characterized as being slow, effortful, serial in nature, and demanding of attentional resources. These qualitative distinctions have often served as a foundation in studies on the acquisition of automaticity.

There are certain difficulties concerning the criteria involved in establishing that a process is automatic. The characteristics that are said to represent automatic processing do not necessarily co-occur hence violating the internal consistency of the concept. For example, letter-encoding which was thought to be automatic, i.e. resource-free and obligatory, has been found to require resources (Paap & Ogden, 1981). Letter-encoding might possess one characteristic of automaticity, i.e. it is obligatory, but this process requires attentional resources. It would seem that the criteria for establishing automaticity should be dissociated from the concept. A process might be considered automatic even if the criteria are not all met. Furthermore, much of the research on automatic processing fails to consider all of the characteristics of automaticity. The present research will only evaluate a subset of characteristics and will therefore be unable to verify if all the criteria have been met. In addition to these difficulties, other researchers have criticized the labelling of improvements in task performance as acquired automaticity (Cheng, 1985; Logan & Stadler, 1991; Ryan, 1983). These issues will be addressed later.

In their research on training reading skills, Frederiksen *et al.* (1985a;

1985b) assumed that a skilled reader possesses more automatic components than a less skilled reader. These researchers have demonstrated that training specific reading components to automaticity is helpful to less skilled readers. They developed instructional systems that were focused on training particular components to automaticity. It was believed that training would ultimately lead to improved reading performance overall by automatizing certain components that previously required processing resources. Developing skill in using contextual information to retrieve and integrate word meanings was one of the lower level components that was trained with an instructional system called SKIJUMP.

The SKIJUMP system was a computerized game in which the goal was to quickly determine if a presented word was semantically appropriate for a given context. A sentence appeared on a computer screen with one of its final words deleted. Then a series of targets were exposed, one at a time, and the subject had to judge the semantic appropriateness of each target. Manipulations included high- and low-constraining contexts, and high- and low-probability words that were semantically related to the context. Semantically unrelated foils were also included. Targets were preceded and followed by visual masking to increase the need to use contextual information. Subjects obtained higher scores when they responded as early as possible upon target presentation. The ability to identify a word that is barely visible required the use of context. Also, when subjects' performance had reached a criterion level <u>during</u> the task this resulted in a decrease in the time between target exposures (executed by the computer program) so that subjects would be compelled to integrate information more rapidly and efficiently. Therefore subjects were continuously challenged as the game progressed. And in order to maintain high performance standards they were required to make the most efficient use of the context to decide on the appropriateness of a word. The faster the subject responded to the targets the higher the score in the game. No score was given for correct rejection of a foil, however an incorrect decision was penalized by decreasing game points. When subjects had mastered the game training was terminated.

Training resulted in faster RTs at judging the semantic appropriateness of targets and foils. Mean RT at the end of training for high-probability words was 430 ms, 572 ms for low-probability words and 1083 ms for foils. Learning curves were typical in that there was a sharp decrease in mean RT following the first session, next there was a gradual decrease and, finally mean RTs asymptoted. However, there was evidence of a speed/accuracy trade-off for foils. It was suggested that the game provided an incentive for responding earlier rather than maintaining a 100% accuracy rate. Despite the improvement in responding to foils, words were consistently responded to faster and more accurately.

Subjects also demonstrated improved performance on a criterion context priming task (pre- vs. post-training) which was analogous to the SKIJUMP task. Measures of judgment accuracy improved significantly (83% on pre- vs. 95% on post-training) for low-probability words. These results indicated that SKIJUMP training had increased subjects' ability to use information contained in context to gain access to semantic memory regardless of probability status. Since the criterion measure involved a unique semantic domain improved performance could not result from the familiarity with sentence context. Subjects must have developed a general facility in using the semantic information to activate concepts in semantic memory. Prior to training subjects were more accurate at rejecting foils in high-constraining contexts (68%) compared to low-constraining contexts (51%). Following training the difference in accuracy between high-constraining (72%) and low-constraining (74%) was negligible. Improvement in foil rejection may be attributable to an increased ability to rapidly evaluate the meaning of words.

Transfer of training was also measured in unit detection, pseudoword and word pronunciation tasks. The components required to process the information in these transfer tasks were not directly trained in SKIJUMP (as they were in other training procedures used by the authors). Only marginal effects of SKIJUMP training on transfer tasks were found. Finally, SKIJUMP training failed to transfer to a real reading situation as measured by the Nelson-Denny Reading Test.

In summary, the SKIJUMP training procedure required subjects to combine perceptual and word recognition skills while concurrently making use of semantic information provided by the sentence to facilitate word identification and semantic interpretation. As SKIJUMP performance improved many skills were developing. For example, the criterion and transfer tasks measured improvements (although marginal) in perceptual encoding of orthographic units in words and word recognition skills, and inference tasks measured improvements in reading and understanding sentence contexts. Improvements in component processing contributed to improved SKIJUMP performance. These results support an interactive componential approach to training reading skills (Stanovich, 1980).

Although Frederiksen and his colleagues have provided a framework for studying the development of reading skills, their interest lies mainly in developing training procedures and not in measuring automatic processing. For example, it was assumed that the assessment of faster RTs and greater response accuracy was indicative of automatic processing of components but these results could simply demonstrate that controlled processing had become more efficient (faster) without necessarily becoming automatic. Subjects could have developed a game strategy as opposed to acquiring automaticity. Although the benefits of their training procedures are obvious, Frederiksen *et al.* did not offer any suggestions concerning learning mechanisms that may be responsible for the changes due to training and whether these learning mechanisms were strategic or automatic.

Purpose of the Study

The goal of the present study was to train one specific reading component to asymptote. Performance changes resulting from training would then be measured on a criterion task involving related components. Finally these changes will be related to learning mechanisms. Specifically, subjects will be trained on a semantic category search task using a procedure that is assumed to develop automaticity. The training will be preceded and followed by a lexical decision task that measures automatic and controlled processing. The category search and the lexical decision tasks involve similar processing components so that the latter criterion task will measure any changes in the components that are associated with training. Learning mechanisms responsible for changes due to training will be addressed in the discussion (Logan & Stadler, 1991). What follows is a description of these tasks.

Category Search Training

The reading component to be trained in the present study is word recognition for which a category search paradigm was used. This task constrained subjects to access semantic memory. The design was based on a visual search paradigm developed by Schneider and Shiffrin (1977; Shiffrin & Schneider, 1977). Briefly, a typical search task involves the presentation of a memory set-frame followed by a test set-frame. The memory set-size usually varies between one and four items. The subject must study the list of items in the memory set and then indicate as quickly as possible whether or not any of the items in the test set-frame matched an item in the memory set. The test frame is composed of distractor items and, potentially, an item from the memory set (the target). Two classes of effects based on the relationship between the distractor and target set have been observed. When the target and distractor items are systematically different from each other (e.g., searching for a letter among digits) this is called *consistent mapping* (CM). In the CM condition a target item can never be a distractor and a distractor is never a target. In this condition when a target item is present in the probe frame it is always responded to positively; the mapping between stimulus and response is consistent. In contrast, when the targets and distractors are not qualitatively different from each other (e.g., searching for a letter among other letters) this is referred to as *varied mapping* (VM). In a VM condition an item is on one occasion a target and on the next, a distractor. In this condition the response to an item can be positive or negative; the mapping between stimulus and response is varied.

It has been demonstrated that whether the task consists of searching for characters (Schneider & Shiffrin, 1977), words, or categories (Fisk & Schneider, 1983; Schneider & Fisk, 1984) CM and VM training produce the same pattern of results, i.e. search task complexity seems to be irrelevant in determining the pattern of results. When given extensive training in search tasks, CM and VM designs produce dissimilar results. VM searches are typically slower than CM searches. VM searches are affected by memory set-size (200 ms per comparison), show only minimal improvement with practice, and searches suffer a deterioration in performance when a secondary task is added. CM searches on the other hand show significant performance improvement with training, are not affected by memory set-size (1.7 ms per category comparison), and suffer only a temporary reduction in resource capacity when a secondary task is added (Fisk & Schneider, 1983). Practice leads to a flattening of RT slopes regardless of memory set-size in CM searches but not in VM searches. VM searches are said to result from controlled processing; serial, slow, effortful, and capacity-limited. Automatic processing is said to evolve from CM searches; parallel, fast, effortless, and not limited by short-term memory. Initially, controlled processing will occur during the performance of a novel task but with *extensive, consistent* practice automatic processing should develop (Fisk & Schneider, 1983; Schneider & Fisk, 1982b; 1982c).

Schneider and Fisk (1984) investigated the development of automatic category search and its transfer. Fisk and Schneider (1983) had previously demonstrated that automatic category search can evolve from a CM design. However, it was speculated that perhaps subjects were learning the category exemplars and not actually performing a semantic search in the

CM condition, since targets were never distractors and vice versa. In other words, if subjects were learning the category exemplars during training (e.g., dog, cat, horse, etc..) they would not have to make a semantic search when they saw the category name (e.g., ANIMAL); they could simply respond positively to the target since it was never a distractor or the targets would appear to "pop out" of the screen (Shiffrin & Schneider, 1977). If this was the case then subjects could have developed a task strategy and not necessarily automatic processing. In addition to answering this question, they wanted to see whether training would transfer to untrained items of the same category. If transfer did occur then they could argue that subjects were in fact performing a semantic search.

In a series of visual search experiments subjects were trained in both VM and CM conditions. The goal of the first experiment was to determine the number of exemplars per category needed to develop asymptotic levels of automatic performance. Subjects were trained in CM4 (4 exemplars per category), CM8, CM12 and VM conditions; different categories were used in each condition. The memory set consisted of a single category name and was followed by a probe containing three items (one target and two distractors). The subjects' task was to locate the target as quickly as possible (top, middle, or bottom of the video display); this way a target could appear on every trial. Results indicated that the CM searches (4, 8, and 12) improved significantly over trials but the VM search did not. It seems that training category searches in a CM condition, regardless of the number of exemplars per category, will lead to asymptotic levels of automatic performance.

The goal of the next experiment was to investigate the transfer of training in CM conditions. In the transfer condition the number of exemplars per category was increased to 12 from either 4 or 8. Thus, if subjects had been trained with 4 exemplars from a category in the first experiment, 8 new and untrained category members (from the trained category) were added and transfer was measured on these new items. In the case where 8 exemplars per category had been trained, 4 untrained exemplars were added. Subjects were also trained on six exemplars in a VM condition and six exemplars from a new category in the CM condition. Results indicated that VM performance did not improve significantly over trials, confirming the findings in the previous experiment. On the other hand, performance significantly improved over trials in all CM conditions. Over the same number of trials, RTs for the exemplars in the new category in the CM condition were significantly faster than RTs in the VM condition. CM training on a subset of exemplars from a trained category resulted in high positive transfer to untrained exemplars from that category. When the trained set-size within a category was 8 exemplars there was the highest percentage (92%) of transfer to the 4 untrained exemplars from that same category; compared to 60% transfer when the trained set-size was 4 exemplars to 8 untrained exemplars for the same category. The difference between the transfer conditions (4 and 8 exemplars) was interpreted as resulting from the following: a) with a smaller trained set-size subjects may be memorizing the exemplars and, b) the training of more exemplars per category would be required to properly activate semantic features of the category which would in turn be beneficial in the search for untrained exemplars. From these experiments it was concluded that automaticity develops as a function of the number of consistently mapped detections at the category level since improvement was determined by the number of trials per category rather than trials per exemplar.

In another series of experiments Schneider and Fisk (1984) added a second, concurrent task to the training procedure to investigate the effects of load on category search and its transfer. In the single-task conditions subjects performed a VM digit search, a CM or, VM semantic category search. In the dual-task condition the VM digit search was the primary task and the category search was secondary. It was hypothesized that CM searches would remain unaffected by a secondary task since one characteristic of automatic processing is that it is undemanding of attentional resources. Thus, CM searches could occur in parallel to a secondary task without any detrimental effects on performance. On the other hand it was expected that there would be a definite performance deterioration in the secondary task, when this task was a VM search.

Results in the dual-task condition revealed that performance on CM searches suffered a temporary decline but with training, performance soon improved. However, when resources were allocated to the primary digit search task the VM category searches were impeded and performance on this secondary task did not improve with training.

In the transfer experiment a dual-task condition was used on every trial; subjects performed digit and category search tasks. If CM training developed automatic processing at the category level it was expected that new exemplars from a trained category would be detected even in dual-task conditions. Results indicated that there was a fairly high positive transfer to untrained exemplars (72%) in CM training condition. Subjects detected untrained CM exemplars significantly better than the exemplars in the VM condition, and exemplars from a new category in the CM condition. Untrained exemplars were detected on average 82% of the time on the first presentation and simultaneous VM digit search suffered a decrement of 5.6%. These results demonstrate that CM training leads to high positive transfer to untrained exemplars even in high-workload conditions.

In summary, the above studies have shown that a) CM category-search training develops automatic processing at the category level, b) that CM searches suffer a temporary decrement in RT when a secondary task is added, and c) CM training provides a potential for the occurrence of transfer of training. Given that the purpose of the present study is to train a component to automaticity then it follows that a CM design should be used.

Learning Mechanisms

Skill acquisition has been demonstrated in a category search task and it has been shown that consistent practice is essential for the development of automatic processing and this is characterized by faster RTs, reduced RT variance, reduced error rate, and an increase in the ability to perform two tasks simultaneously. Although CM training results have been associated with the development of automatic processing and VM training results have been associated with controlled processing, not all researchers agree with this interpretation. For example, it has been argued that CM training might compel subjects to develop strategies as opposed to developing automatic processing. As previously noted, subjects might learn the category exemplars in which case they would not be developing automatic processing. The following section addresses criticisms and theories of performance change related to the memory search task.

Schneider and Fisk (1984) proposed a coactivation strengthening hypothesis to explain their CM training and transfer results. Learning in the CM training results from differential strengthening of context nodes. These nodes are activated by the experimental situation and they are not under direct subject control, i.e. they are autonomous (excitation without intention). Since targets can never be distractors, they are not ignored but the distractors are repeatedly ignored. By consistently detecting targets, target nodes become strengthened. On the other hand, by consistently rejecting distractors, distractor nodes are inhibited. It would seem therefore that consistent practice is required for developing automaticity. Also, transfer would occur in the CM condition because the target context becomes activated as opposed to activating the target word exclusively. Performance would not improve in the VM condition because there is no differential activation between nodes; a target is not consistently a target and therefore no strengthening can occur. Automaticity is the product of strengthening of category nodes.

Schneider (1985) has extended the coactivation strengthening hypothesis. He proposed that performance improvement in the CM paradigm is associated with the transition from an initial controlled processing phase to a final automatic processing phase. The proposed model states that processing results from the transmission of messages between processing units. It is argued that consistent mapping between stimulus and response influences the strength of association between processing units. Learning evolves from the enhancement of message transmission power through consistent practice. Increasing message transmission power results in the reduction of transmission time (increasing in speed) and fewer errors. The transmission message power of distractor items should not change or perhaps should even diminish whereas the transmission power between consistently mapped targets should become stronger. Learning in the CM design would lead to the final phase of development which involves automatic processing. Since learning is dependent on consistent stimulus-response relations, VM training should remain in the controlled processing phase.

Cheng (1985) and Ryan (1983) have criticized the interpretation of the results from the memory search studies (Schneider & Fisk, 1984; Fisk & Schneider, 1983; & Shiffrin, 1977; Shiffrin & Schneider, 1977). For example, Cheng disagrees with the claim that improvements in performance in CM training are necessarily due to the development of automaticity. She proposes a strategy-based theory of learning. It was suggested that changes in performance could be attributed to a restructuring of task components rather than to the development of automaticity; the procedures involved in processing the task components are reorganized into new, more efficient procedures. For example, subjects could develop an efficient category-tag strategy in the memory search paradigm that would enable them to respond quickly in the CM condition. The category-tag strategy enables subjects to look up the category tag of the displayed words and simply locate the target. In other words subjects could either be learning the consistently mapped targets or they are probably using a category strategy so that when an untrained target appears (from a consistently mapped category) they will associate the target to the category-tag. Since the category-tag strategy would be inefficient for VM searches these would never improve with training. Transfer to untrained exemplars is predicted in both CM and VM training to the extent that the exemplars are well-learned items. However, Schneider and Fisk (1984) did not investigate transfer of training in the VM condition.

Logan (1988) has suggested that automaticity reflects the transition from an algorithm-based performance to performance based on direct, single-step memory retrieval. This theory makes no assumptions about resource capacity to explain automaticity. In Logan's theory of automaticity each encounter with a stimulus represents an instance, and each instance is stored in memory and retrieved independently. Initially a response to a stimulus is algorithm-based, then with training, the response to the stimulus becomes a race between algorithm and direct memory retrieval; the fastest path wins. Finally, memory retrieval dominates the algorithm. Learning is associated with the accumulation of instance which produce a gradual change from algorithm-based to memory-based performance. Since memory retrieval is based on the number of individual instances that have accumulated, transfer of training (to untrained items) should not occur. Thus, the transfer results in memory search tasks are problematic for the instance theory. It should be emphasized that Logan's (1988) theory stresses that the transition to direct memory retrieval requires repeated exposures to a consistent set of task components. The importance of consistent practice on the development of an efficient mechanism has also been stressed by others (Anderson, 1982; MacKay, 1982).

To briefly summarize although researchers do not all agree with Schneider and Fisk's (1984) interpretations of the memory search results, most would agree however that consistent practice is required to develop automatic processing or to at least produce changes in task performance.

According to the instance theory if each encounter with a stimulus is stored in memory then it is feasible that automatization has no limits. The idea that automaticity follows a continuum has been supported by Logan (1988), Klapp, Boches, Trabert, and Logan (1991) and MacLeod and Dunbar (1988). These researchers have found that automaticity is not simply an all-or-none phenomenon. Their training studies have provided evidence for a continuum view of automaticity. If the development of automaticity follows a continuum then changes in task performance should be apparent on a criterion task that is presented prior to and after training. The criterion task should possess related components to the training task. If performance is considered automatic prior to training (i.e., if the component is already automatized) the magnitude of automatic processing effects should be larger following training. The criterion task used in the present study will be used to assess the magnitude of automatic and controlled processing effects following training.

Primed Lexical Decision Task

Primed lexical decision tasks have been used to study the nature of word recognition and semantic memory (Antos, 1979; Burke, Diaz, & White, 1987; Favreau & Segalowitz, 1983; Neely, 1976; 1977). Though Seidenberg, Waters, Sanders, and Langer (1984) (also Balota & Chumbley, 1984) have questioned the use of the lexical decision task as a valid indicator of word recognition, by making the claim that a lexical decision involves post-lexical access, this paradigm is still commonly used to isolate the word cognition component. In this type of task subjects must decide whether or not a letter string forms a real word. According to Coltheart, Davelaar, Jonasson, and Besner (1981; also den Heyer, Goring, Gorgichuck, Richards, & Landry, 1988) the mental lexicon must be accessed in order to decide upon the 'wordness' of a letter string especially when the nonwords are legal, i.e. when the nonwords resemble real words and are pronounceable. It is assumed that there are at least two processes involved in recognizing a word. One process involves matching the word's visual features to an internal representation in the mental lexicon. And the second process involves attaching the appropriate meaning to the lexical entry (Becker, 1980; Morton, 1969; 1979). In an activation metaphor of lexical access it is further assumed that word recognition is achieved when the activation threshold of a word unit is exceeded (McClelland & Rumelhart, 1981; Morton, 1969). If no word unit has been activated above some criterion threshold then the decision is to opt for a nonword (den Heyer, Goring, Gorgichuck, Richards, & Landry, 1988).

Connectionnist models of word recognition assume there is no need to postulate the existence of a mental lexicon (Seidenberg & McClelland, 1989). According to the model, recognition results from a specific pattern of spreading activation through several layers of features (phonological, orthographic, or semantic) that represent the stimulus-word as opposed to activating one word unit in a lexicon. Despite this alternative approach to explaining human cognition Neely (1990) argues that this model has yet to fully explain semantic priming effects.

In a typical primed lexical decision task a prime precedes the target letter string. When a target word is preceded by a semantically related word (e.g., DOG-cat, ANIMAL-dog, BREAD-butter) subjects make faster lexical decisions, i.e., RTs are faster than if the target followed a semantically unrelated word (Favreau & Segalowitz, 1983; Neely, 1977; 1976). This is known as semantic priming.

The paradigm used in this study was similar to that of Burke *et al.* (1987) (see also Favreau & Segalowitz, 1983; Neely, 1977). A primed lexical decision task was used to investigate semantic facilitation and inhibition resulting from automatic and controlled processing. It was therefore necessary to isolate automatic processing from controlled processing and this was achieved by using three techniques. One of these was the manipulation of the stimulus-onset asynchrony (SOA), i.e., the time interval between the offset of the prime and the onset of the target. Automatic processing is typically isolated from controlled processing at very short SOAs. Favreau and Segalowitz (1983) found that automatic processing occurs at SOAs as short as 200 ms[1]. In addition, Neely (1977) found that facilitation resulting from automatic processing seemed to be inactive at SOAs of 700 ms or greater, suggesting that spreading activation decays unless sustained by attention. On the other hand, controlled processing appears to be effective at longer SOAs (of at least 410 ms or longer). Therefore, to obtain automatic facilitation an SOA of 410 ms or less should be used. To isolate facilitation resulting from controlled processing an SOA of at least 700 ms or more should be used (guaranteeing decay of automatic spreading activation).

Two other techniques used for isolating automatic processing from controlled processing are a) the manipulation of subjects' expectancy and b) prime-target relatedness (see Table 1). For the *expectancy* manipulation, subjects are instructed to expect a target that is related or unrelated to the prime. However, subjects are also shown targets that are unexpected. Subjects' expectancies have been found to increase or decrease RTs in lexical decision tasks. Favreau and Segalowitz (1983) found that subjects responded significantly faster to expected targets than to unexpected targets at the long SOA. In addition, subjects' expectancies have been made to vary

[1] Burke *et al.* (1987) used a short SOA of 410 ms, while Neely (1977) used a short SOA of 400 ms. Both reported obtaining automatic facilitation.

Table 1

Relatedness and Expectancy Conditions in a Primed Lexical Decision Paradigm

	EXPECTANCY	
	Expected	Unexpected
PRIME-TARGET RELATEDNESS		
Related	ANIMAL - dog (RxR)	SPORT - hockey (RxU)
Unrelated	SPORT - maple (UxU)	ANIMAL - hammer (UxR)

The RxU and UxR conditions indicate unexpected trials.

orthogonally with prime-target relatedness (Burke *et al.*, 1987). The *relatedness* manipulation pertains to whether the prime is semantically related or unrelated to the target. In the case where the prime and target are related, the target (e.g., dog) is from the category indicated by the prime (e.g., ANIMAL). In the case where the prime and target are unrelated, the target (e.g., apple) is an exemplar from a category other than the one indicated by the prime (e.g., ANIMAL). It has been found that subjects' RTs are faster for semantically related targets than for unrelated targets at the short SOA, and faster to related items that are expected at the long SOA (Favreau & Segalowitz, 1983; Neely, 1977).

When the SOA, expectancy, and relatedness manipulations are combined the effects ensuing from automatic and controlled processing are as follows (Burke *et al.*, 1987; Favreau & Segalowitz; 1983; Neely, 1977):

1) It has been found that when subjects are instructed to expect a target related to the prime (e.g., ANIMAL-dog) and they get such a target, there is facilitation. This facilitation is said to result from automatic processing at the short SOA and controlled processing at the long SOA. At the short SOA, automatic activation has not yet decayed and it has spread to related targets, resulting in facilitation. At the long SOA, the subject's attention is maintained on the related targets, resulting in facilitation.

2) When subjects are instructed to expect a target unrelated to the prime (e.g., ANIMAL-apple) and they get such a target then there is

facilitation at the long SOA. This is said to reflect controlled processing, at the long SOA only. Subjects have time to shift their attention to targets from the semantically unrelated category and this results in facilitation. However, no facilitation is found at the short SOA because there is insufficient time for the slow acting controlled processes to operate, i.e., the subject does not have enough time to shift attention to the unrelated, yet expected, target category. Note that automatic processing, which is only measured at the short SOA, is effective only when the target and the prime are semantically related.

3) When subjects are instructed to expect a related target (e.g., ANIMAL-dog) and see an unrelated target (e.g., ANIMAL-apple) there is no facilitation, only inhibition at the long SOA. This occurs because subjects have to shift their attention, after having been maintained on the expected relationship, and this shifting results in inhibition. Automatic processing effects are facilitory, not inhibitory and no facilitation is expected for unrelated targets.

4) When subjects are instructed to expect an unrelated target (e.g., ANIMAL-apple) and they see a related target (e.g., ANIMAL-dog) there is facilitation at the short SOA (reflecting automatic processing), and inhibition at the long SOA (resulting from controlled processing). At the short SOA spreading activation to semantically related targets automatically occurs resulting in facilitation. However, at the long SOA

subjects have already shifted their attention to the semantically unrelated category, thus when a related target appears attention must be re-shifted, resulting in inhibition. At the long SOA, automatic spreading activation has decayed. Thus the benefits arising from automatic spreading activation at the short SOA for recognizing semantically related, yet unexpected, targets are not present at the long SOA.

To recapitulate, at the short SOA there is inhibitionless facilitation for related targets only, regardless of expectancies, and this is thought to reflect automatic processing. The short SOA was set at 150 ms in the present study to ensure that expectancy would not influence responding. At the long SOA, there is facilitation for *expected* targets and inhibition for *unexpected* targets regardless of prime-target relatedness and this is thought to be a result of controlled processing. The long SOA in the present thesis was set at 1900 ms to ensure that automatic spreading activation has decayed and that expectancy would influence decision time (see Table 2 for a summary of these effects). In Table 2 the '+' signs indicate a facilitation effect in word recognition and this is measured by faster RTs (compared to a baseline). The facilitation effects result from both automatic and controlled processing. The '-' signs indicate an inhibition effect in word recognition which is measured by slower RTs (compared to a baseline). Inhibition effects result from controlled processing only. The blank areas in this table represent conditions in which automatic and controlled processing are

Table 2

Predicted Effects of Automatic and Controlled Processing by SOA, Expectancy and Relatedness

	EXPECTANCY			
	Expected		Unexpected	
PRIME-TARGET RELATEDNESS	Auto.	Control.	Auto.	Control.
	150 ms (short SOA)			
Related	+		+	
Unrelated				
	1900 ms (long SOA)			
Related		+		-
Unrelated		+		-

Auto. = predicted automatic effects
Control. = predicted controlled effects
+ = Speeding of RT (facilitation)
- = Slowing of RT (inhibition)

presumed to have no influence on response time. According to Burke, *et al.* (1987) the same pattern of controlled processing effects found at the long SOA can also be obtained at the short SOA. They claim that the attentional effects (reflecting controlled processing) are small and are not always found at a short SOA. This claim, however, contradicts much of the speculation that controlled processing effects are usually found at a long SOA only. Neely's (1977) research has revealed that controlled processing effects are slow acting and require sufficient time to operate, at least 410 ms. Therefore, calculations of controlled processing effects will be limited to the long SOA and calculations of automatic processing effects will be restricted to the short SOA in the present thesis. Using a short SOA of 150 ms in the present study will ensure that the slow acting controlled processing effects are not in operation. These calculations will be addressed later in the introduction.

Many of the previously described effects obtained in the primed lexical decision task have been explained via automatic spreading activation. This particular mechanism is adequate for explaining the facilitation effects resulting from automatic processing. However, it fails to explain inhibition effects resulting from controlled processing. In the following section several semantic priming mechanisms will be described. They each attempt to clarify certain elements of the primed lexical decision task.

Semantic Priming Mechanisms

Although several theories have attempted to describe the mechanisms involved in semantic priming no one single theory has managed to explain all of the inhibition and facilitation effects obtained in the present paradigm. According to dual-process theory (Collins & Loftus, 1975; Posner & Snyder, 1975b) the prime activates information in semantic memory and this activation automatically spreads to related concepts, thereby lowering the activation threshold of these concepts. In other words, when a semantically related target follows the prime it is rapidly acted upon because the concept (word) has been activated and the threshold has been lowered. When the prime and the target are related there is semantic facilitation and this is thought to be a result of automatic processing. However, when the prime and the target are unrelated semantic facilitation can occur only if the subject's attention has been shifted to the unrelated concept, i.e. by instructing the subject to think of an unrelated concept. Semantic facilitation in this case is thought to be a result of controlled processing. Automatic spreading activation theory can account for facilitation effects but not for inhibition effects such as in the unexpected-related condition at the long SOA.

A second theoretical mechanism proposed assumes that a prime establishes an expectancy set consisting of potential targets semantically related to the prime. If a target is part of the expectancy set then recognition is faster than if it were not part of the set, such as when the prime and target are semantically unrelated (Becker, 1979; 1980; 1985). In Becker's verification model of word recognition a prime establishes a semantic set. When a target appears the search begins in the semantic set for a match of features while a sensory set is concurrently being established. If there is a match between the stimulus and an item in the semantic set a 'word' response is given. If no match is found then stimulus analysis proceeds to the sensory set. If a match is found in the sensory set then a 'word' response is given; if no match is found a 'nonword' decision is made. This theory can account for facilitation and inhibition effects for semantically related category-target relationships found in the lexical decision task, as well as instruction-induced priming (Neely, 1990). However, it fails to explain the facilitation obtained in the unexpected-related condition at the short SOA. The verification model would predict an inhibition effect since the subject prepares an internal semantic set based on instructions. The target (being unexpected yet related) would not be part of the 'prepared' semantic set. If verification on the 'prepared' set reveals no match then the analysis proceeds to the sensory set. Hence, the predicted inhibition effect.

In both the dual-process and the expectancy-set theories the processes are assumed to be pre-lexical because priming is said to speed access to the lexicon thus facilitating target recognition. In contrast another set of mechanisms that are said to account for these effects are referred to as "post-lexical" (Balota & Chumbley, 1984; Chumbley & Balota, 1984; Seidenberg, Waters, Sanders, & Langer, 1984). It has been suggested that facilitation effects of related primes are pre-lexical, whereas i hibitory effects of unrelated primes are post-lexical (Lorch, Balota, & Stamm, 1986). Others have suggested that post-lexical processes are effective only after the lexicon has been accessed for the target entry and they facilitate by speeding lexical selection and decision. Two mechanisms are briefly discussed below and they can account for many, but not all, of the effects found in the primed lexical decision task used in the present study.

In Norris' (1986) plausibility-checking theory, priming context helps in the selection of a plausible entry once lexical access has occurred. Thus on a 'word recognition time continuum' the influence of the priming context is located after lexical access but prior to conscious word recognition. Facilitation results when the prime and target are related because the recognition threshold is lowered (contextually plausible). When the target and prime are unrelated inhibition ensues since the recognition threshold is raised (contextually implausible). This model can also explain the facilitation effect obtained in the expect-unrelated condition at the long SOA. Subjects have time to build a contextually plausible set containing features of expected, yet unrelated items. However, the problem with this model is that it fails to explain why facilitation is not followed by inhibition in the unexpected-unrelated condition at the short SOA.

A second post-lexical theory is advanced by Ratcliff and McKoon (1988). Their compound cue theory assumes that, upon presentation, the prime and target join together to form a compound cue that is used to access recognition memory. The strength of the connections between items in memory and the compound cue determine a familiarity value. Once access occurs the compound cue's familiarity value is what ascertains the lexical decision. The greater the familiarity value the more likely the decision will be 'word'. The lower the familiarity value, the higher the probability of a 'nonword' decision. The intermediate familiarity values require more detailed analysis. Priming in the compound-cue model results from a high familiarity value between related items. The priming strength is dependent on the prime-target compound cue and not solely on the prime, via spreading activation as in the automatic spreading activation model. As a matter of fact in this theory the prime only plays a passive role inasmuch as it is connected to the target, in contrast to the automatic spreading activation model where the prime plays quite an active role in speeding lexical access.

The concept of familiarity values has also been employed by Balota and Chumbley (1984) in their investigation on lexical decisions (however they proposed a familiarity/meaningfulness (Chumbley & Balota, 1984) model of word recognition that minimizes the necessity for lexical access).

The compound cue theory can easily account for the facilitation effects of related primes. One also assumes that in unrelated yet expected conditions, subjects generate an 'internal' prime and with the target form a compound cue thus producing facilitation in the expect, yet unrelated condition. This explains facilitation in the long SOA. Facilitation for unexpected yet related targets at the short SOA can be accounted for by assuming that the subject has no time to generate an internal 'prime' to form a compound cue with the target and therefore uses the presented prime with the target to form a cue.

This thesis does not attempt to solve the debate on whether semantic priming is pre- or post-lexical nor does it plan to resolve whether making a lexical decision requires accessing the mental lexicon. These issues are nonetheless relevant in explaining the effects obtained in the primed lexical decision task.

Neutral Prime

In most studies using a primed lexical decision task (e.g., Favreau & Segalowitz, 1983; Neely, 1976; 1977) neutral primes are used to calculate the net effects of automatic and controlled processing, also referred to as cost-benefit analysis of RT (Antos, 1979). In other words, if for the same target the RT following a word prime was faster than the RT following a neutral prime, then this was taken as evidence of a facilitation effect (benefit). On the other hand, if for the same target the RT was slower following a word prime than a neutral prime this was taken as evidence of an inhibition effect (cost). However, the 'neutrality' of the neutral prime has been questioned (Antos, 1979; Burke *et al.* 1987; de Groot, Thomassen, & Hudson, 1982; Jonides & Mack, 1984). Evidence suggests that whether the neutral prime is a string of letters (*XXXXX*), the word "*NEUTRAL*" or the word "*BLANK*", the potential exists for underestimating or overestimating facilitation and inhibition effects. For example, facilitation would be underestimated at the short SOA if target processing is delayed because processing of the prime is incomplete when the target appears. De Groot *et al.* (1982) found that subjects expected primes to be words so that when they saw a nonword prime (e.g., a row of Xs) they treated the target as a prime and this effect slowed response times to targets. This resulted in underestimating inhibition effects and overestimating facilitation effects. Therefore, the paradigm used in this study omitted the use of the neutral prime. Although omitting the neutral prime has also raised some concerns (Neely, 1990), Burke *et al.* (1987) have demonstrated how automatic and controlled processing can be measured without the use of the neutral prime (see Table 3). On the one hand, automatic processing, as previously noted, occurs at the short SOA and produces a facilitation effect for related targets only (regardless of expectancies). Hence, the net effects of automatic processing are calculated by collapsing across all expected and unexpected trials, within the relatedness conditions, and subtracting the latency for related trials from unrelated trials. Facilitation is said to have occurred

Table 3

Calculating Automatic and Controlled Processing Effects without a Neutral Prime

Prime-Target Relationship	SOA			
	SHORT		LONG	
	Expected (same)	Unexpected (different)	Expected (same)	Unexpected (different)
Related	**RxR**	**RxU**	**RxR**	**RxU**
Unrelated	**UxU**	**UxR**	**UxU**	**UxR**

Automatic Processing Effects = Unrelated - Related
Short SOA only

(UxU + UxR) - (RxR + RxU)

Controlled Processing Effects = Unexpected - Expected
Long SOA only

(RxU + UxR) - (RxR + UxU)

when the mean latency for related trials is smaller than the mean latency for unrelated trials. On the other hand, controlled processing occurs at the long SOA and produces facilitation or inhibition depending on expectancy, regardless of prime-target relatedness. To measure a controlled processing net effect, related and unrelated trials are collapsed within the expectancy conditions, then mean RT on expected trials is subtracted from the mean RT on unexpected trials. If the difference is significant then controlled effects are said to have occurred.

Questions addressed in this Thesis

The purpose of the present study was to examine the effects of training on the development of automatic word recognition skills. In order to explore this issue a consistently-mapped-category-search training procedure was implemented. As discussed earlier, the CM design has been used to train the automatic processing of components. To examine whether the CM design had successfully trained automatic processing a second task was implemented. This task, a primed lexical decision task, was administered prior to and after training. The design that was used in this study was similar to one used by Burke *et al.* (1987). A formula, developed by Burke *et al.* (1987), was used to assess automatic and controlled processing net effects that occur in the lexical decision task. One of the benefits associated with the use of this specific design is that these net effects could be calculated for each subject. Task performance results will address the following questions: Does CM training develop automaticity? And does training transfer to untrained exemplars of a trained category? Does the lexical decision task detect the acquisition of automatic net effects produced by CM training? And can these effects be detected in a single subject?

The CM category search RTs were expected to decrease significantly and asymptote as a result of training. A concern in the training procedure is that subjects might memorize the targets and somehow ignore the prime. Therefore, surprise trials were added to ensure that processing of the prime would facilitate locating the target in the display. A surprise trial consisted of an exemplar that was related to the prime but it was only seen about six times throughout the entire training procedure (in contrast, trained words were seen 124 times). If subjects were following the instructions and fully processing the category name, then RTs to surprise items should become as fast, with practice, as RTs to trained items. On the other hand, if subjects were memorizing the exemplars then Rts to surprise items should not decrease in comparison to RTs to trained items.

Automatic and controlled net effects were calculated using the Burke *et al.* (1987) formulae. In order to eliminate the possible confusion of obtaining controlled processing effects at the short SOA (as did Burke and colleagues) this was set at 150 ms. An increase in the automaticity net effect was expected following training. Controlled effects were not expected to change since CM training should develop automaticity. Nonetheless, a smaller net effect due to controlled processing might be observed following training since RTs to related items are expected to decrease. As noted earlier, controlled effects are obtained by subtracting the mean RT of expected items (related + unrelated) from the mean RT of unexpected items (related + unrelated). During training subjects receive consistently-mapped, semantically-related trials. Therefore, subjects always obtain what is expected, and what is expected is always related. In the post-training lexical decision task expect-related (xR) items should be responded to faster. If training results in a general improvement in response times for all conditions, and specifically for the related items (RxR and RxU) this might result in a decrease in the post-controlled net effects. In other words the post-controlled net effect might be smaller than the pre-controlled net effect. A 2-way within analysis of variance will be performed on the group data to measure the differences between pre- and post-training net effects. Analyses will also be conducted on the pre- and post-effects for each subject and these analyses will be compared to subject's performance on the training task.

Finally, results for the lexical decision task are expected to replicate the typical pattern of lexical decision task effects discussed earlier. Overall, collapsing across the pre- and post-training lexical decision RTs, at the short SOA RTs to related items are expected to be faster than to unrelated items, regardless of expectancy. In contrast, at the long SOA, RTs to unexpected items should still be slower than RTs to expected items, regardless of relatedness. If transfer of training occurs then untrained and trained items should exhibit a pre-post decrease in RTs.

Method

Subjects

Eight students - three women and five men, aged 31 to 52 - from Concordia University volunteered for this study and were paid five dollars an hour for their participation. The subjects' first language was English and their mean reading rate was 216 words/minute with 85% comprehension in the screening procedure (described below). Each session lasted one hour for a total of 11 hours per subject. The implications underlying the use of a small sample size will be addressed in the result section.

Materials and General Procedure

In addition to the screening procedure, there were three phases in the experiment: 1) the first phase involved a memory task and a primed lexical decision task, 2) the second phase consisted of the training task which lasted a total of 8 hours and, 3) the final phase involved the reintroduction of the memory task and the primed lexical decision task. All of the above tasks were carried out on an Apple IIe computer. The procedures were initiated by the experimenter from one computer, which controlled the sessions and recorded subjects' RTs and accuracy. The subjects had their own monitor (Apple IIe) and a remote control box on which to record their answers. Subjects were instructed to use their preferred hand in all phases of the experiment when manipulating the control box.

Screening Procedure

The screening procedure was essentially a reading task. This task required subjects to read texts in English so as to assess their reading proficiency, and then answer multiple-choice questions pertaining to the texts so as to assess their reading comprehension[2]. There were three texts; one practice and two test texts. The practice text was of narrative type and this was followed by five multiple-choice questions. One of the two test texts was an expository type and the other was a narrative type. The texts were selected from similar scientific magazines and were assumed to be equal in terms of difficulty. Each text was followed by 13 multiple-choice questions. Prior testing had revealed that the multiple-choice questions could not be answered correctly at more than chance accuracy without having previous knowledge of the texts. The average length of the test texts was 956 words.

[2] For the purpose of creating our own screening procedures, texts were selected from scientific magazines and multiple-choice questions were prepared.

Subjects were instructed to read the texts silently and as quickly as possible without sacrificing comprehension. Once the subject had initiated the task, by pressing the appropriate button on the control box, a page of text appeared on the monitor. After having read the portion that appeared on the screen the subject would press the appropriate button on the box to call up another page of text. No button allowed them to return to previously read portions. Following each text presentation was a series of multiple-choice questions. Subjects' reading proficiency, for both texts, was measured in words per minute and their comprehension was measured as percentage of accura · ıy answered questions.

Testing Stimuli

All of the stimuli used in this study originated from the Favreau and Segalowitz (1980) and Battig and Montague (1969) norms. The Favreau and Segalowitz norms were obtained by asking students to write, in order of preference, four items that best represented a particular category. In selecting items for :his study instances that comprised two words (e.g., koala bear) were eliminated. Six categories and 18 representative exemplars were chosen to form two target lists in the memory and lexical decision tasks. Two lists were created to ensure that the potential observed effects could be generalized to the chosen categories in both lists and not only to one list in particular. No main effect of list was expected. Subjects were required to read through a list of <u>all</u> potential targets in this study (even those that were not in their set) to ensure that they recognized and knew the meaning of each word (see Appendix A).

Memory Task

Pilot testing on the primed lexical decision task revealed that some subjects completely ignored the prime in long stimulus onset asynchrony (SOA) conditions regardless of the instructions given. It is crucial to the logic of the primed lexical decision task that the prime be processed because of the advantage it confers on the RT of the lexical decisions. Thus, it was necessary to create a preliminary task that forced subjects to focus on the prime as a predictor of the target, especially in the unrelated condition (e.g., see the prime ANIMAL and think of the category TREE). For this purpose a simple memory task was given before each block of primed lexical decision trials. Each list of word-word pairs in the memory task comprised the same prime-target relatedness condition as the ensuing lexical decision task.

In order to create lists for the memory task five of the initial 18 exemplars from the six selected categories were chosen. Each of the exemplars was paired with a related or unrelated category. For example, if the instructions in the ensuing lexical decision task were to expect related items (e.g., see ANIMAL and expect animal) then the memory list would contain related category-exemplar word pairs. If, on the other hand, the instructions were to expect unrelated items (see ANIMAL and expect a type of tree), then the memory list would contain unrelated category-exemplar word pairs. Together four word lists were created, each containing 10 category-exemplars pairs (see Appendix B). Two word lists contained related category-exemplar word pairs and the two others contained unrelated category-exemplar word pairs, for each target list (A and B). These five exemplars were reasonably representative of the category to which they belonged but they were items which would not appear as targets in the subsequent lexical decision task. The category-exemplar pairs were randomized so that each time the subject studied the list (until recall), the pairs were in a different order. The goal was to have the subject remember category-exemplar relationships rather than order of presentation. Subjects were given a brief study period of 30 seconds after which they were required to recall the pairs. They were given 50 seconds to write them. Once the subjects had recalled the list of words three successive times they would then proceed to the appropriate primed lexical decision testing block.

Lexical Decision Task

Thirteen representative instances from the original set of 18 exemplars were used in this task (see Appendix C). In the lexical decision task the prime was always a category name whereas the target words were always category exemplars. Pronounceable and orthographically legal nonwords were created by changing one letter in each of the target words. The position of the letter that was changed varied across targets. Since the nonword was created directly from the target word it had the same number of letters and syllables.

From each of the two lists of words, two testing blocks of 64 prime-target pairs were created (see Table 4). One testing block contained *related* items and the other contained *unrelated* items. Each block contained 32 prime-target word pairs and 32 prime-target nonword pairs.

There were four types of trials; one type of trial consisted of expect-related (xR) targets in which subjects saw a target that was related to the prime. This was called a related-expect-related (RxR) trial. A second type of trial consisted of expect-unrelated (xU) targets in which subjects saw a target that was unrelated to the prime and expected. This was called an unrelated-expect-unrelated (UxU) trial. The last two types of trials included unexpected trials. Essentially, subjects were instructed to expect one type of target but saw another. One type was called unrelated-expect-related (UxR) trials; subjects expected a related target but saw an unrelated target. The other type was called related-expect-unrelated (RxU) trials; subjects expected an unrelated target but saw a related target.

Within the *related* testing blocks there were 52 RxR trials - 48 test trials and 4 buffer trials - and 12 UxR trials. Within the *unrelated* testing blocks there were 52 UxU trials - 48 test and 4 buffer trials - and 12 RxU trials. Thus, 81% of the time subjects expected a particular type of target and saw it, and 19% of the time they expected a particular type of target and were shown an unexpected target.

Table 4

Testing Blocks in the Primed Lexical Decision Task

	EXPECTED	UNEXPECTED	TOTAL
RELATED	RxR (26)	RxU (6)	32
UNRELATED	UxU (26)	UxR (6)	32

TARGET LIST A

	EXPECTED	UNEXPECTED
RELATED	ANIMAL-animal (13) FRUIT-fruit (13)	SPORT-sport (3) VEGETABLE-vegetable (3)
UNRELATED	SPORT-tree (13) VEGETABLE-tool (13)	ANIMAL-flower (3) FRUIT-clothing (3)

TARGET LIST B

	EXPECTED	UNEXPECTED
RELATED	SPORT-sport (13) VEGETABLE-vegetable (13)	FRUIT-fruit (3) ANIMAL-animal (3)
UNRELATED	FRUIT-tool (13) ANIMAL-tree (13)	SPORT-flower (3) VEGETABLE-clothing (3)

1) The number in brackets indicates the number of word trials for that condition.

2) The words in uppercase indicate the category type used and the words in lower case indicate the category from which the exemplars were taken.

In the *related* testing block subjects were instructed to expect a target word related to the prime. In the *unrelated* block subjects were instructed to expect a target unrelated to the prime and they were given the appropriate unrelated target category. Subjects were instructed to indicate whether the target was a word or a nonword and to respond as quickly and as accurately as possible. Each block of trials was seen twice, once with a long SOA and once with a short SOA. The relatedness manipulation was blocked; there was a related (expect-related) testing block and an unrelated (expect-unrelated) testing block. The SOA was also blocked. Thus, there were four blocks of trials; long SOA (expect-related), long SOA (expect-unrelated), short SOA (expect-related), and short SOA (expect-unrelated). Since the same 'expect-related' block of trials was seen at the short and long SOAs, the prime-target pairs were randomized. The order in which these blocks occurred was counterbalanced across subjects. One group of four subjects received target list A and the other group of four received target list B.

Each trial began with the presentation of a fixation cross for 1000 ms, followed by a prime (50 ms), followed by a blank screen and finally a target word appeared (2048 ms). The prime always appeared in upper case letters whereas the target always appeared in lower case letters (see Figure 1). The SOA was either short (150 ms) or long (1900 ms). The first four trials of each block were buffer trials consistent with the instructions given for

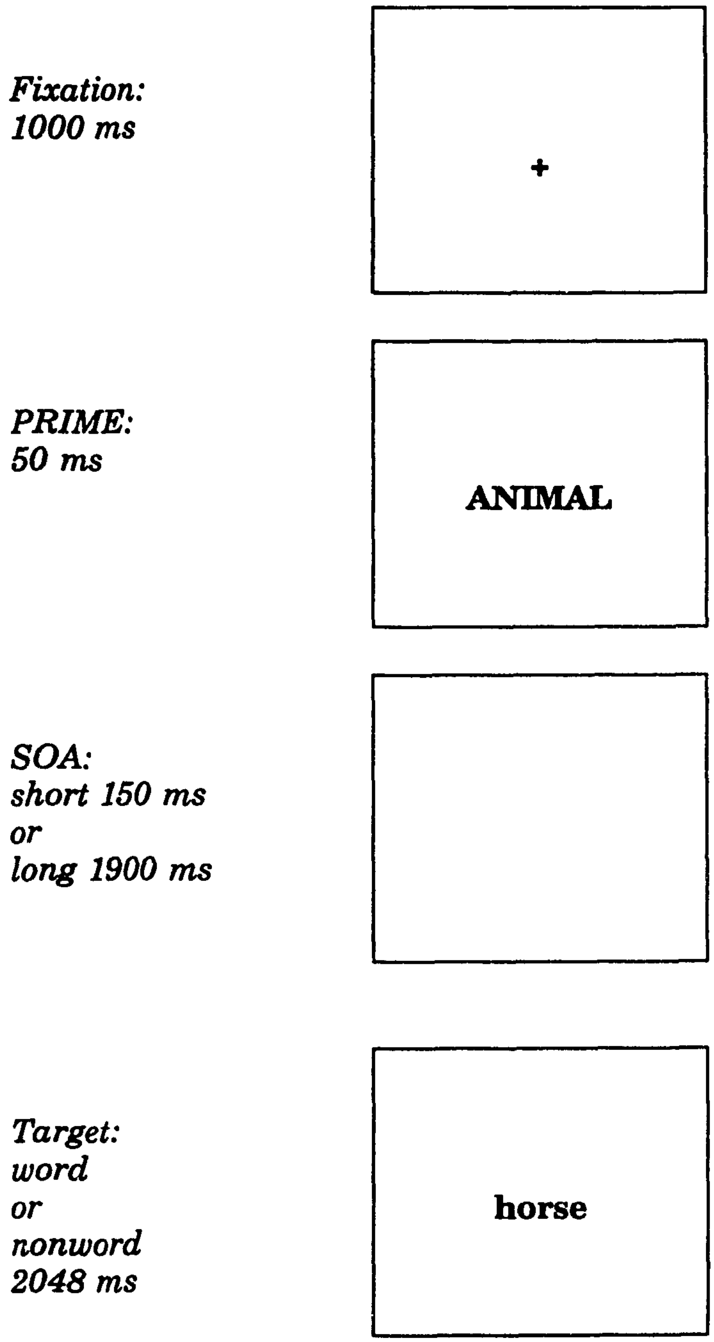


Figure 1. Example of a primed lexical decision task trial.

that block (i.e., the buffers never included unexpected trials).

To summarize, there were four types of trials combining semantic relatedness between the prime and target (semantically related or unrelated) and subjects' target expectancies (expected or unexpected). In addition, the trials were blocked into long and short SOAs. The prime was always a category name (word) and the target was either a word or a nonword. Subjects saw only two category names per block of trials.

Training Procedure

The training procedure consisted of a semantic category search task. Subjects were trained on old categories (expected category exemplars from the lexical decision task) and new categories (unexpected category exemplars from the lexical decision task). All the words chosen for the search task (targets and distractors) were 3 to 8 letters in length and were ranked between 1 and 40 for typicality in the Favreau and Segalowitz (1980) and Battig and Montague (1969) norms.

From two categories in the expected conditions (UxU and RxR) used in the lexical decision task, seven of the 13 exemplars were chosen for the training task. These seven items were repeated four times during each training session for a total of 124 times for the 31 sessions. From the remaining six exemplars, five were selected to appear at a rate of one item per training session. These five exemplars were referred to as surprise items and were seen at least six times each throughout the entire training procedure. It was necessary to insert surprise items to see if subjects were reading the prime (category name) or simply memorizing the target words. Only one item from the original set of 13 was actually untrained in each of the trained categories. These will be referred to as *untrained exemplar from a trained category*. The exemplars from the two other categories in the expected conditions were untrained and will be referred to as *untrained category items*.

Other trained items were selected from the unexpected conditions (RxU and UxR) in the lexical decision task. Only three of these items are seen in the lexical decision task so nine additional items were chosen from the norms to obtain a set of 12 exemplars for the purpose of training. Seven of the 12 exemplars were seen 124 times, and the other five were seen at least six times (surprise items).

The four target categories for series A were; four-legged animal, clothing, sport, and tool. Those chosen for series B were; flower, fruit, tree, and vegetable. The distractor items were chosen from categories that never appeared in the memory frame of the training task. They were selected from among the 14 most representative items in the following categories; drink, dwelling, fabric, furniture, metal, part of the human body, vehicle, and weapon (see Appendices D and E). These items were selected from the norms mentioned earlier. The same distractors were used for both target lists.

Subjects were shown a memory-set frame, consisting of a single category name, followed by a target display list. The category name was displayed for 50 ms. The target display, consisting of three items, would then appear and remained on the screen for approximately 2 seconds (2048 ms) or until the subjects responded. On every trial only one of the three items in the target display was semantically related to the category name. For example, a trial could consist of a memory frame with the category name *ANIMAL* and this would be followed by the target display containing *boat, horse, cotton.* Only one item is semantically related to the category in the memory frame and the other two items are distractors (see Figure 2). The subject's task was to locate the position of the related item by pressing the appropriate button on the control box (in this example the subject would press the middle button). The distractor items were chosen from categories that had never appeared as primes or as category names in the memory frame. The target items were thus consistently mapped, i.e., target items were never used as distractors and the distractors items never appeared as targets.

Each training session began with 10 buffer trials for orientation purposes; these data were not used in the final analyses. After every 16th trial the subject was given feedback pertaining to accuracy and mean RT for the past 16 trials. The feedback was printed at the bottom of the screen. Beginning with the second set of 16 trials, and for every ensuing set of 16

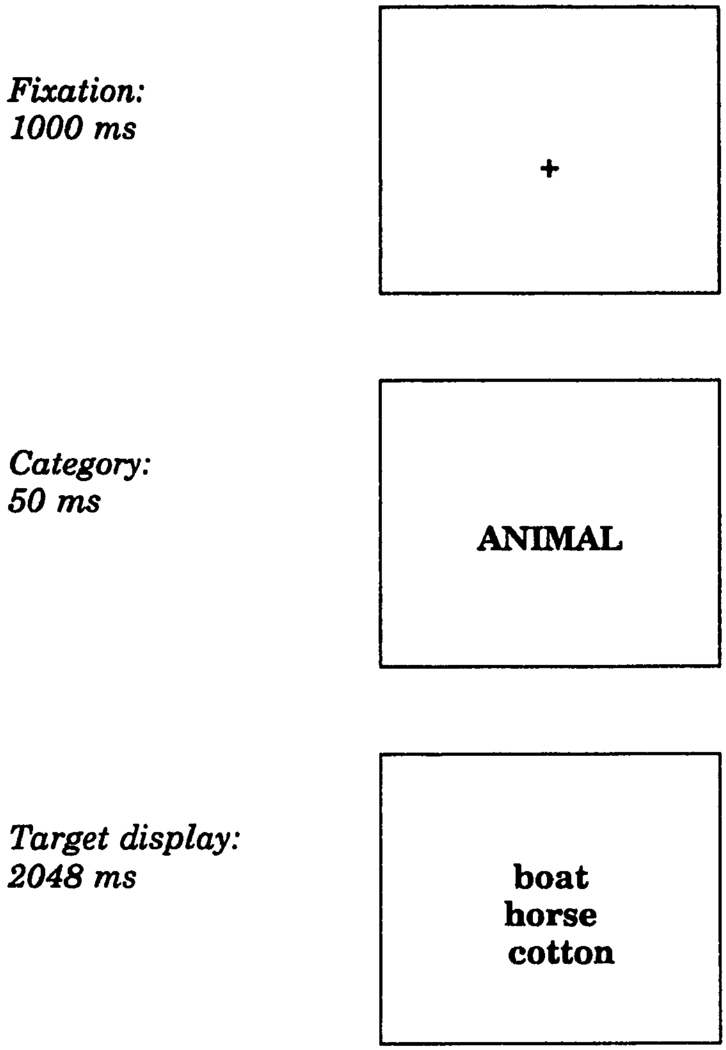


Figure 2. Example of a consistent mapping trial.

trials until the end of the session, subjects were given updates of their performance based on the last 16 trials along with the accuracy/RT feedback. For example, if they had decreased their mean RT by 25 ms from the previous set they would read "GOOD, GETTING FASTER", if they had increased their mean RT by 25 ms they would read "GETTING SLOWER", and if the change in RT was less than 25 ms from the previous set they would read "ABOUT THE SAME SPEED".

There were 31 training sessions in total but the first served as practice and the other 30 sessions were used for the following analyses. After the final training session the memory task and primed lexical decision task were reintroduced. For this part of the lexical decision task, the untrained exemplars from the trained categories were shown again as targets in order to see if transfer of training had occurred.

Results

RTs to words and nonwords in the lexical decision task data set that were found to be extreme (at least two standard deviations from the mean) were replaced with values that were two standard deviations from the mean. Less than 4% of the words and nonwords were outliers. Only correct response RTs in the lexical decision and category search tasks were used in the following analyses. The number of incorrect responses was used to calculate error rates and RTs over 2048 ms were eliminated from further analyses, resulting in the exclusion of a total five response times across all eight subjects.

The words used in the lexical decision and CM search tasks were divided into four levels on the Training factor. The trained level refers to exemplars that were seen 124 times during training. The surprise level refers to exemplars that were seen on average 6 times during training. The untrained level refers to exemplars that were never seen during training. Within the untrained level some exemplars belonged to a trained category (untrained exemplars from a trained category) and others to an untrained category (untrained exemplars from an untrained category). The untrained exemplars from a trained category were used to assess whether transfer of training occurred.

Did the CM training result in automatic processing?

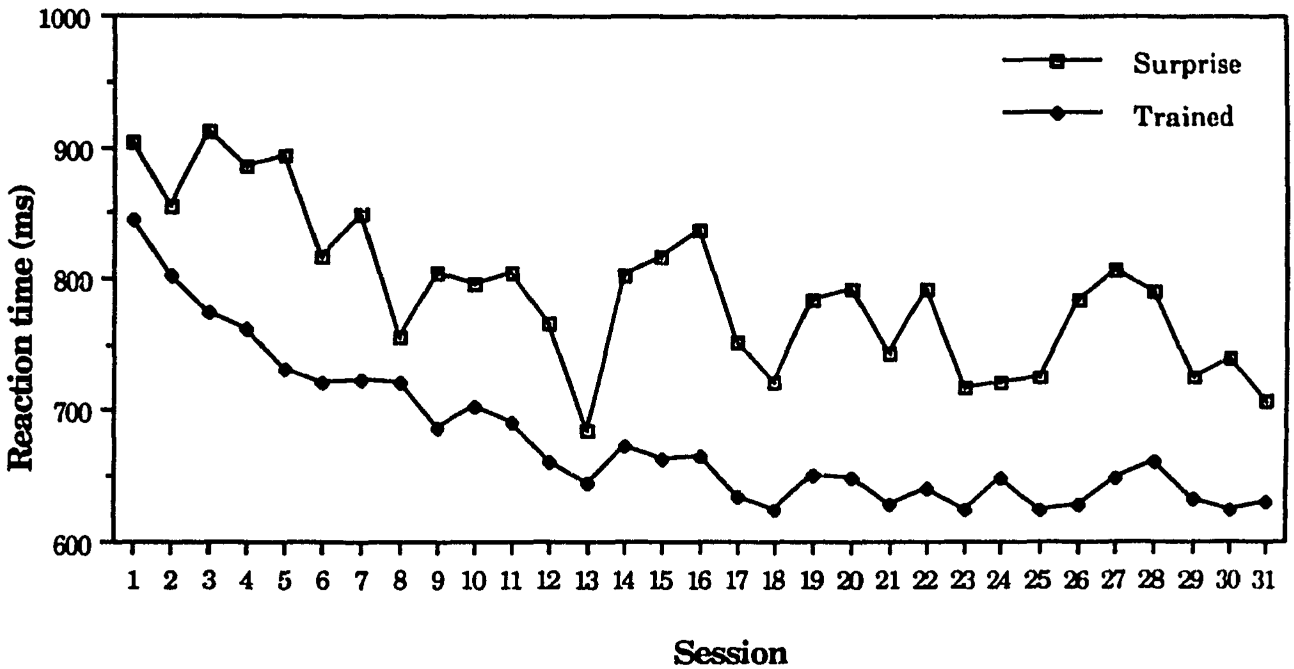
In order to answer this question the training data were analyzed as follows. First, a regression analysis was conducted on mean RTs as a function of training. Linear regressions were also performed on RT standard deviation scores and accuracy scores as a function of training. These analyses served to indicate whether or not training resulted in significantly reducing mean RTs, RT standard deviation scores and increasing accuracy scores. Second, a regression analysis on mean RTs, as a function of training, was conducted specifically on sessions two to 13.

Inspection of Figure 3 reveals that up to session 13 mean RTs decreased substantially compared to the mean RTs in the ensuing training sessions where they seemingly asymptoted. And t[illegible]d, a regression analysis was conducted on mean RTs to surprise items as a function of training. The reason for analyzing surprise item RTs was to evaluate subjects' performance (e.g., their compliance with the instructions) and to examine whether or not items seen on average six times profited from training.

The first training session (session one) served as practice so it was excluded from further analysis. Note however that session one was included in Figures 3, 4, and 5 to show initial improvements in task performance which is indicated by a decrease in mean RT. Also in the following section, when training results are addressed, the first training session to be included in the analysis will be referred to as session two (2). In addition to excluding the first training session the first ten trials per training session were omitted from the analyses; these served to help subjects become adjusted to the task.

Trained Item Analysis (30 sessions) Regression analysis indicated that there was a significant correlation ($\underline{r}$=+.86) between mean RT for trained items and training ($\underline{F}$ (1,28) = 73.806, $\underline{p}$ <.001). Training accounted for 74% of the variance in mean RT for sessions 2 to 31 (see Figure 3). There was a 4.79 ms improvement in RT per session (at 100 trials/session).

Regression analysis of the RT standard deviation scores revealed that



<u>Figure 3</u> Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task.

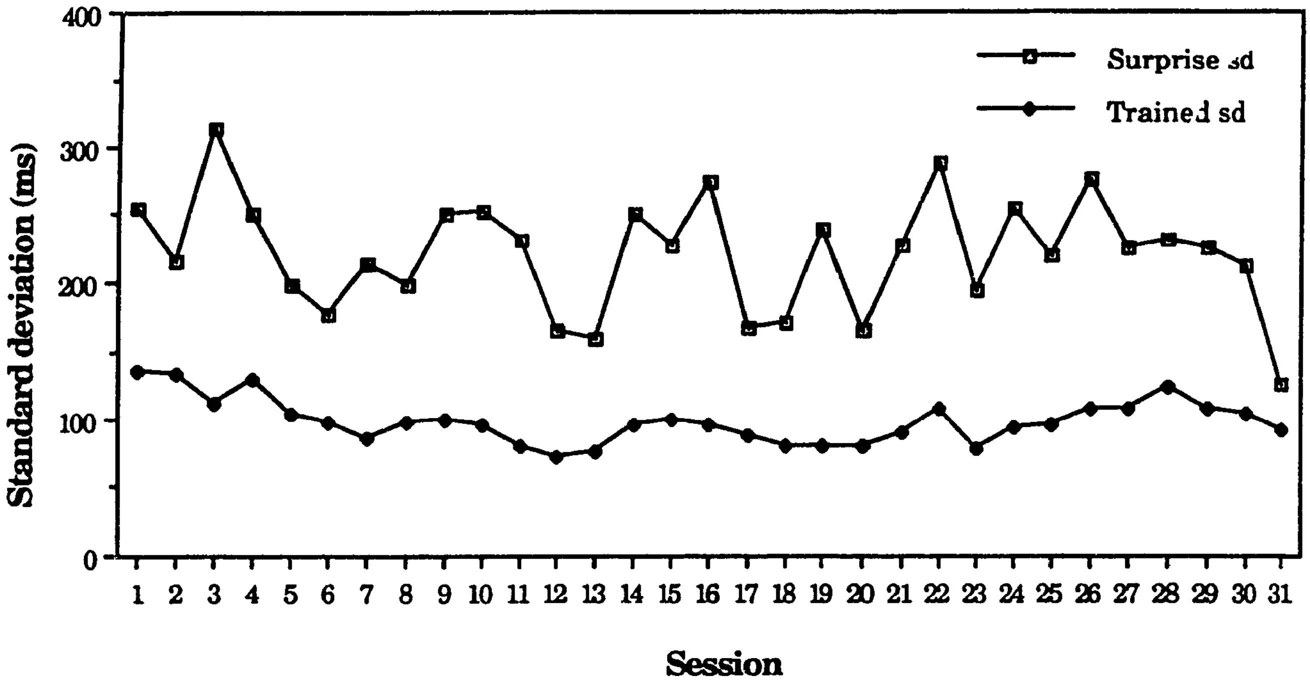


Figure 4 Standard deviation (ms) per session as a function of training for surprise and trained items in the category search task.

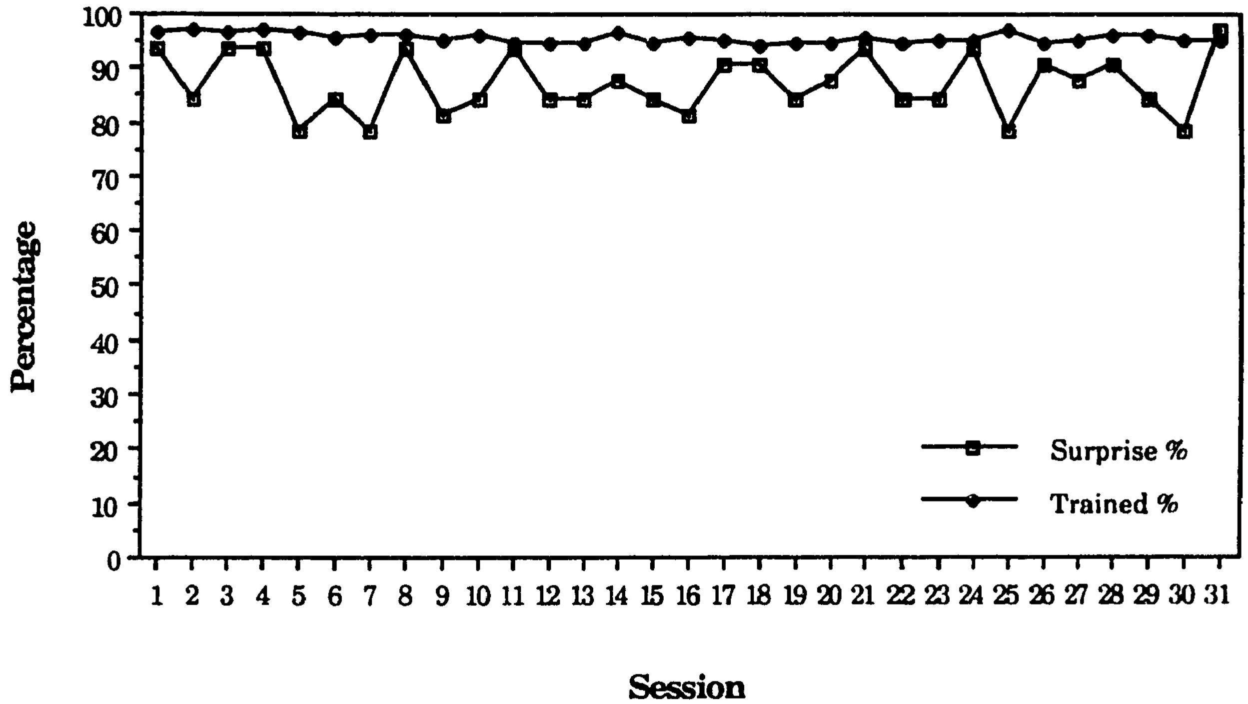


Figure 5 Percentage of correct responses as a function of training for surprise and trained items in the category search task.

the correlation (r=+.62) between standard deviation and training sessions was also significant (F (1,28) = 17.397, p <.001) (see Figure 4). The mean standard deviation improvement per session was 0.88 ms.

The correlation between response accuracy and training (r=+.42) was marginally significant (F (1,28) = 5.839, p <.022). The improvement in response accuracy with training was 0.04% per session (see Figure 5).

Overall, these analyses indicate that subjects' mean RTs and RT standard deviation scores decreased significantly with training for sessions 2 to 31. The marginal improvement in response accuracy indicate that there was no speed/accuracy trade-off.

Figure 3 clearly shows that the mean RT per session for the group of subjects asymptoted around the 13th session. There was a sharp decrease in mean RTs up to session 13. The decrease in mean RTs for training sessions following session 13 was gradual. Given this observation, further analyses were conducted on the block of sessions showing the greatest decrease in mean RT, specifically sessions 2 to 13 (which consist of a single block of 12 sessions).

Trained Item Analysis (12 sessions) The regression analysis on this specific block of sessions (2 to 13) revealed that mean RT correlated significantly (r=+.97) with training (F (1,10) = 141.695, p <.001). Training accounted for 94% of the variance in mean RT between sessions 2 and 13 (note that session one is considered as practice and is not accounted for in these analyses). There was a 12.24 ms improvement in RT per session. Regression analysis on mean RT as a function of training on session 14 to 31 indicated that training correlated (r=+.49) only marginally with mean RT (p <.04). The mean RT slope for these sessions was -1.47 ms. A clear illustration of a linear decrease in RT as a function of training is shown in Figure 6. This figure demonstrates a linear trend in the decrease in mean RT as a function of training sessions when the 30 training sessions are blocked into sessions of 5. Both mean RTs and standard errors are indicated for the trained and surprise items.

Regression analysis on RT standard deviation scores for sessions 2 to 13 revealed a significant correlation (r=+.76) between RT standard deviation and training (F (1,10) = 13.918, p <.004). The RT standard deviation slope for these training sessions was -2.73 ms. The RT standard deviation slope for the sessions following session 13, i.e. 14 to 31 was +0.006 (p >.9).

Regression analysis on response accuracy scores revealed that accuracy correlated significantly (r=+.89) with training for sessions 2 to 13 (F (1,10) = 36.674, p <.001). The correlation between response accuracy and training was r=+.12 (p >.6) for the following training sessions (14 to 31).

Together, the analyses performed on the data for the trained items indicate that training resulted in significantly decreasing mean RTs and RT standard deviation scores. However, further analyses revealed that much of the variance in mean RTs (94%) was accounted for by training in sessions 2

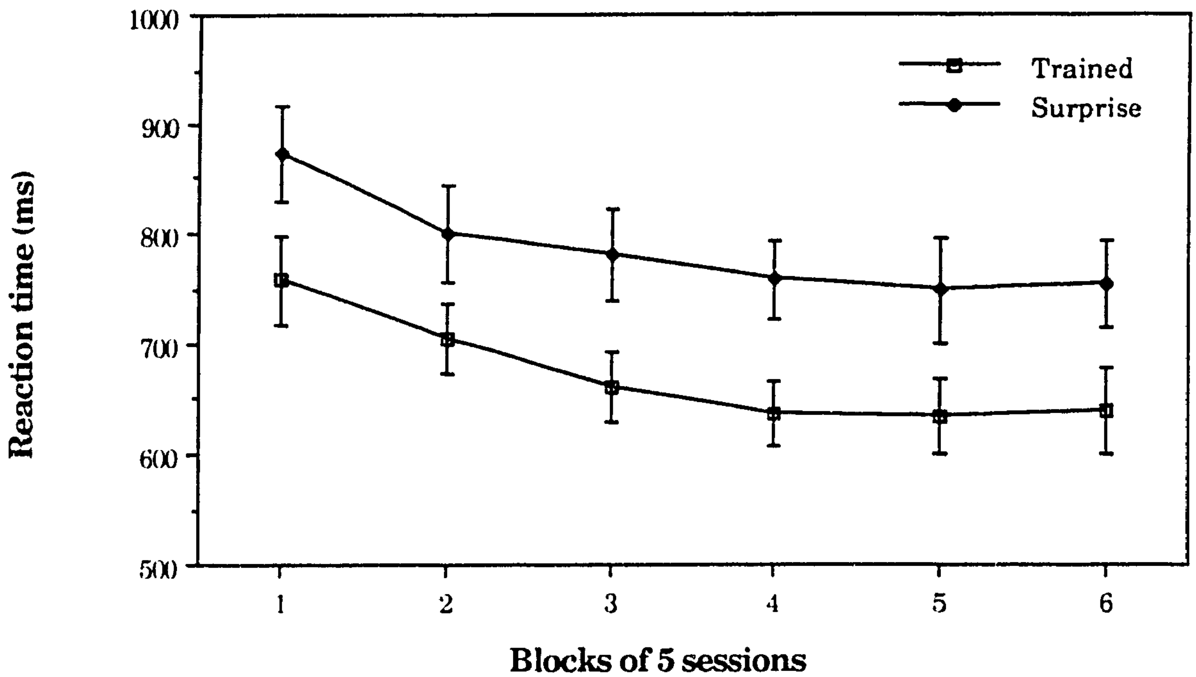


Figure 6 Mean reaction time (ms) and standard error as a function of blocks of 5 sessions for trained and surprise items in the category search task.

to 13. The significant decrease in mean RT and RT standard deviation scores and the significant increase in accuracy scores was accounted for by the first 1300 trials (sessions 2 to 13). Following session 13 training did not seem to help subjects in substantially improving their mean RTs, RT standard deviation scores or response accuracy.

Surprise Item Analyses (30 sessions) A regression analysis of mean RTs for the surprise items as a function of training revealed that training accounted for 45% of the variance in mean RT. There was a 4.36 ms improvement in mean RT per session. The correlation between mean RT and training (r=+.67) was significant (F (1,28) = 22.756, p <.001) (see Figure 3).

Analysis of RT standard deviation scores as a function of training indicated that the variance did not decrease or stabilize with time, resulting in a correlation of r=+.11 (F = (1,28) = 0.357, p >.55) (see Figure 4). Though mean RTs to surprise items decreased with practice there was some fluctuation across sessions which affected the variance scores.

In order to examine whether mean RTs to surprise items followed a pattern similar to the mean RTs for trained items, regression analyses were conducted on mean RTs to surprise items as a function of training for sessions 2 to 13.

Surprise Item Analyses (12 sessions) These analyses revealed that mean RT for surprise items correlated significantly with training (r=+.85) (F

(1,10) = 24.945, p <.001). Training accounted for 72% of the variance in surprise item RTs within these sessions. RT mean improvement per session was 15.24 ms. In the subsequent sessions (14 to 31) the improvement in mean RT was 3.60 ms per session (p <.05). Analyses of RT standard deviation and response accuracy for surprise items indicated that neither of these factors correlated significantly with training.

Overall, these analyses show that training significantly decreased mean RTs to surprise items. Also, as with the results from the trained item analyses, training accounted for much of the variance (72%) in mean RT to surprise items in sessions 2 to 13. These results could be taken as support for automaticity. However, since RT standard deviation scores for surprise items were inconsistent caution must be exercised in interpreting these results as direct evidence of automatic processing. In addition, given the relatively moderate number of trials (1300 trials) at which asymptote appeared to have occurred it is reasonable to speculate that further training might have helped RTs to reach a lower asymptote. This issue will be addressed in the discussion. The following section addresses questions concerning the estimates of automatic and controlled processing net effects as measured by the lexical decision task.

Did the CM training result in automatic processing net effects in the lexical decision task?

In order to measure effects resulting from training, automatic and controlled processing net effects were estimated in the pre-training (PRE) and post-training (POST) conditions using the Burke *et al.* (1987) formulae. The data from the lexical decision tasks (PRE and POST) were used to calculate these effects. First, to calculate automatic processing net effects the mean RT for *related* trials was subtracted from the mean RT for *unrelated* trials at the short SOA. Second, controlled processing effects were calculated by subtracting the mean RT for *expected* trials from the mean RT for *unexpected* trials at the long SOA.

Two separate ANOVAs were conducted to evaluate differences in the PRE- and POST-automatic and controlled processing net effects. One 2x2 ANOVA focused on automatic net effects while the second 2x2 ANOVA focused on controlled net effects. There were two within factors: Phase (PRE and POST) and Training (trained and untrained). In these analyses the untrained category items and the untrained exemplars from a trained category were collapsed. In addition, simple t-tests were conducted on each of the net effects to evaluate whether they were significantly different from zero.

Group analyses ($\underline{N}$ = 8) The 2x2 ANOVA conducted on the automatic net effects indicated that the main effects of Phase and Training were not significant. The difference between the PRE- and POST-automatic net effects for the trained items and the untrained items was not significant. The Phase x Training interaction was not significant. A two-tailed t-test conducted on the automatic net effects indicated that for the trained items both the PRE- and POST-automatic net effects were significantly different from zero ($\underline{t}$ $(7) = 3.16$, $\underline{p} < .02$, and $\underline{t}$ $(7) = 3.78$, $\underline{p} < .01$, respectively). For the untrained items only the PRE-automatic net effect was significantly different from zero ($\underline{t}$ $(7) = 4.33$, $\underline{p} < .01$) (see Table 5).

The results demonstrated that for the trained items automatic net effects did not increase following training but these effects were still significantly different from zero. Though training might not have increased automatic processing effects it did not significantly diminish these effects, as measured by the lexical decision task. On the other hand, automatic effects for untrained items were not significantly different from zero in the POST condition. Untrained items clearly did not profit in any way from training and the automatic processing effects were even reduced.

The 2x2 ANOVA conducted on the controlled net effects revealed a marginally significant Phase main effect. The PRE-controlled net effect (80.34 ms) was significantly larger than the POST-controlled net effect (0.83 ms) ($\underline{F}$ $(1,7) = 5.381$, $\underline{p} < .05$). There was also a significant Phase x Training interaction ($\underline{F}$ $(1,7) = 13.549$, $\underline{p} < .008$). This interaction arises from a large decrement between the PRE-controlled net effect (101.96 ms) and the POST-

Table 5

Automatic and Controlled Processing Net Effects (in ms) for Trained and Untrained Items for N = 8 resulting from the Burke *et al.* (1987) formula

		Net Effect (in ms)	
Phase	N	Automatic	Controlled
		Trained items	
Pre	8		
M		106	102
SD		95	103
Post	8		
M		93	-32
SD		69	72
		Untrained items	
Pre	8		
M		110	59
SD		72	208
Post	8		
M		38	34
SD		107	145

controlled net effect (-32.18 ms) for the trained items. However, the decrement between the PRE-controlled (58.71 ms) and POST-controlled (33.84 ms) net effects for the untrained items was negligible.

Training seems to have significantly reduced the controlled net effects in the POST condition for the trained items. Since related items were trained, even the items that were unexpected (yet related) in the lexical decision task would seem to have profited from training. The reduction in mean RT for each of the four components in the equation were examined and the following pattern was obtained: the decrease in mean RT between the PRE and POST net effects for the RxU (211 ms) and UxR (303 ms) was greater than the reduction in the RxR (102 ms) and UxU (144 ms) conditions. Consequently, the difference between the latency for unexpected items and latency for expected items was greatly reduced. Not only was it reduced, but given the negative POST-controlled net effect it is clear that response latency for unexpected items was shorter than latency to expected items. Nonetheless, this POST-controlled net effect for the trained items was not significantly different from zero. On the other hand, the PRE-controlled net effect was significantly different from zero ($\underline{t}$ (7) = 2.80, $\underline{p}$ <.05). Finally, no significant difference was observed between the PRE- and POST-controlled net effects for the untrained items. Table 5 illustrates the net effects of automatic and controlled processing for trained and untrained words obtained for $\underline{N}$ = 8. It could be argued that, following training, the

Expectancy manipulation in the lexical decision task was ineffective.

Did the CM training result in automatic processing net effects in the lexical decision task? And were these effects detected in a single subject?

The rationale for using a small sample in the present experiment was to examine training effects and the impact of training on automatic and controlled processing for each individual. If, following training, the lexical decision task detected changes in automatic processing as measured by the Burke *et al.* (1987) formulae then the lexical decision task could potentially be used as a tool for measuring the acquisition of automaticity in a single subject.

Individual Analyses (n = 1) Group analyses of the training data revealed that mean RT asymptoted around session 13. However, not all subjects asymptoted at the same mean RT, or around the same session. Each subjects' training data was graphed to uncover at which session mean RT asymptoted: five subjects asymptoted around the 13th session, two asymptoted around session 15, and finally one asymptoted around session 17. Regression analyses were conducted on each subject's training data to further verify if training correlated significantly with mean RT for surprise and trained items within the sessions showing the greatest decrease in response latency. These analyses will be related to the estimates of automatic and controlled processing effects obtained for each subject.

To evaluate automatic and controlled processing net effects for each subject, the lexical decision task data (PRE and POST) were analyzed in separate ANOVAs ($\underline{n} = 1$) where target items were treated as "subjects" for purposes of analysis. Two three-way ANOVAs were conducted on each individual's data: one at the long SOA and one at the short SOA. At the long SOA there were two between factors: Expectancy (expected and unexpected) and Training (trained and untrained) and one within factor: Phase (PRE and POST). The Phase factor is considered as a 'within' factor because each of the target items was seen twice. Individual word RTs were collected for the same target items in the lexical decision task, prior to and following training. These analyses would indicate if there were any differences in controlled processing net effects resulting from training. At the short SOA the two between factors were Relatedness (related and unrelated) and Training and the within factor was Phase. These analyses would indicate differences in automatic processing net effects.

Not all of the individual effects will be reported here. It should be noted that mean response latency for one subject (JG) was very inconsistent. Although this subject's mean RT decreased significantly with training, the learning curve never smoothed out. It was speculated that because this subject was on cold medication during some of the training sessions this could have hindered her performance. Nonetheless, her data were not excluded from any of the group analyses since sample size was small.

Upon inspection of the net effects for each subject (see Appendix F), MC produced some of the highest estimates. Regression analyses on MC's training data revealed a significant correlation between mean RT and training ($\underline{r}$=+.985) for sessions 2 to 17 ($\underline{F}$ (1,14), 471.025, $\underline{p}$ <.001). Training accounted for 97% of the variance in mean RT. Also, a significant correlation between mean RT to surprise items and training was found ($\underline{r}$=+.77) ($\underline{F}$ (1,11) = 15.827, $\underline{p}$ <.002) for sessions 2 to 14. Analysis of variance on MC's latencies revealed a significant main effect of Relatedness at the short SOA ($\underline{F}$ (1,45) = 5.871, $\underline{p}$ <.02). Related items had faster RTs (642 ms) than unrelated items (734 ms). There was also a main effect of Phase at the short SOA ($\underline{F}$ (1,45) = 46 955, $\underline{p}$ <.001. RTs to items in the POST condition (613 ms) were significantly faster than RTs to items in the PRE condition (756 ms). No Training effect was found at the short SOA for automatic processing. A main effect of Phase was also found at the long SOA ($\underline{F}$ (1,41) = 23.77 $\underline{p}$ <.001). Words in the POST condition (639 ms) were responded to faster than in the PRE condition (782 ms). No Training effect was found at the long SOA measuring controlled processing. As speculated in the introduction the POST-controlled effect are smaller than the PRE-controlled effects. This subject was faster on related items regardless of Expectancy.

DW produced high net effects as well. The regression analysis on this subject's mean RTs indicated that training accounted for 88% of the variance in mean RTs for sessions 2 to 13. The correlation between training and mean RT for these sessions was r=+.94 (F (1,10) = 74.008, p <.001). Analysis of variance at the short SOA revealed a main effect of Training (F (1,38) = 11.66, p <.002). Trained items were responded to significantly faster than untrained items (664 ms and 780 ms, respectively). There was also a main effect of Phase (F (1,38) = 7.839, p <.008) indicating that RTs in the POST (685 ms) were significantly faster than RTs in the PRE (790 ms) condition at the short SOA. There was also a main effect of Phase at the long SOA (F (1,45) = 8.227, p <.006). RTs were faster in the POST (726 ms) than in the PRE (841 ms) condition.

It is interesting that subjects producing some of the highest automatic and controlled effects also show strong correlations between training and mean RT, until mean RT asymptotes. On the other hand, subject AB might not have produce the smallest effects, but this subject's regression analysis revealed that training did not correlate significantly with mean RT. To further corroborate this finding the main effect of Phase in the analysis of variance on Short and Long SOAs for AB was not significant.

The only strong trend in the analysis of variance was a Phase main effect at the long SOA demonstrated by six subjects and seven subjects at the short SOA. Otherwise, no consistent pattern of main effects or interactions was found. The mean RTs for trained items for seven subjects were significantly correlated with training (see Appendix G). Further reference to these results will be addressed in the discussion.

The following question concerns transfer of training to untrained exemplars of a trained category.

Did transfer of training occur?

To examine the effects of training on untrained exemplars from a trained category a 2x2x4 ANOVA was conducted on the lexical decision task data. There was one between factors: List (A and B), and two within factors: Training (surprise, trained, untrained category items and, untrained exemplars from a trained category) and Phase (PRE and POST). A significant Phase main effect was found ($\underline{F}$ (1,6) = 29.113, $\underline{p}$ <.002) indicating that RT was significantly faster in the POST condition (612.72 ms) than in the PRE condition (712.85 ms). A significant Training main effect was found ($\underline{F}$ (1,6) = 7.390, $\underline{p}$ <.002) (see Figure 7). Scheffé's post-hoc test revealed a significant difference between response latency to surprise items (635.73 ms) and untrained exemplars (699.68 ms) ($\underline{p}$ <.01). There was also a significant difference between trained item (643.32 ms) and untrained exemplar response latencies (699.68 ms) ($\underline{p}$ <.05). Although there was a significant reduction in mean RT overall, no significant difference was found between mean RTs for untrained category items and untrained exemplars

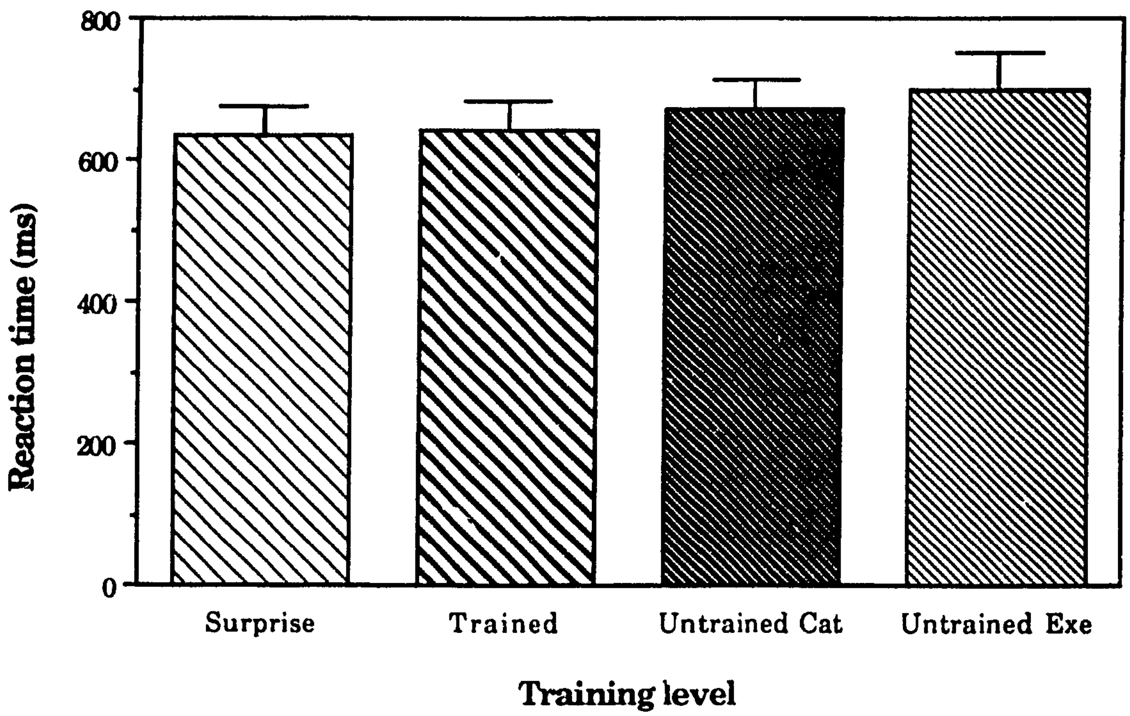


Figure 7 Mean reaction time (ms) and standard errors as a function of training level in the lexical decision task.

from a trained category. Had untrained exemplars from a trained category profited from training through transfer, a significant difference should have been observed between mean RTs for untrained category items and untrained exemplars. This result indicates that untrained exemplars from a trained category did not benefit from training since transfer did not take place.

The following section deals with questions pertaining to the primed lexical decision task.

Did the lexical decision task produce the expected effects of Relatedness and Expectancy?

This section addresses the question of whether the lexical decision task produced the expected effects of Relatedness and Expectancy in the PRE- and in the POST-lexical decision tasks. For this a 2x2x2x2 analysis of variance with one between (List: A and B) and three within variables: SOA (long and short), Relatedness (related and unrelated) and, Expectancy (expected and unexpected) was carried out on the data from each Phase of the lexical decision task.

PRE condition Analyses on the PRE-lexical decision task data revealed a significant main effect of Relatedness ($\underline{F}$ (1,6) = 38.538, $\underline{p}$ <.001). Mean RT to related items (687 ms) was significantly faster than mean RT to unrelated items (787 ms). There was a significant Relatedness x

Expectancy interaction in which related items were responded to significantly faster than unrelated items when they were expected (671 ms and 703 ms respectively) (F (1,6) = 5.991, p <.05). The SOA x Relatedness interaction was not significant (p >.1), neither was the SOA x Expectancy interaction (p >.1).

POST condition The same analysis as above was conducted on the POST-lexical decision task data. A significant SOA x Expectancy interaction was found, F (1,6) = 12.484, p <.01. At the long SOA expected words were responded to significantly faster than unexpected words (601 and 627 ms, respectively). This is an expected effect of the lexical decision task at the long SOA. However, unexpected items were responded to significantly faster than expected items at the short SOA (584 and 622 ms, respectively). This latter result is unexpected in the primed lexical decision task.

Overall, the results from the word analyses failed to replicate all of the expected effects characterizing the primed lexical decision task.

Did the lexical decision task produce the expected effects of Phase? Nonword Analyses

Nonwords were analyzed to reveal whether nonword RTs were faster in the POST- than in the PRE-lexical decision task. If indeed subjects were faster in the POST-lexical decision task on nonwords this would indicate response improvement despite training since nonwords were not trained. Nonwords were created by changing one letter in each of the targets, so each nonword had an analogous word. If a word was related to the prime, the comparable nonword was also classified as 'related'. Consequently, differences between 'related' and 'unrelated' nonwords, as well as 'expected' and 'unexpected' nonwords (Favreau & Segalowitz, 1983) were examined.

A 2x2x2 analysis of variance was conducted on the nonwords. There were three within factors; Phase (PRE and POST), Relatedness (related and unrelated) and Expectancy (expected and unexpected). The List factor was collapsed for nonword analyses since there was no List main effect in the word analyses.

Phase A significant main effect of Phase was found in which RTs were significantly faster in the POST (641 ms) than in the PRE (766 ms) condition ($\underline{F}$ (1,7) = 83.049, $\underline{p}$ <.001). Subjects were either becoming more skilled at the task or were becoming familiar with the nonwords.

Relatedness and Expectancy A main effect of Relatedness was found with mean RT for 'related' nonwords (690 ms) being significantly faster than mean RT for 'unrelated' nonwords (717 ms) ($\underline{F}$ (1,7) = 9.368, $\underline{p}$ <.02). However, an interesting result is the main effect of Expectancy where xU (expect-unrelated) nonwords (691 ms) were responded to significantly faster than xR (expect-related) nonwords (716 ms) ($\underline{F}$ (1,7) = 5.678, $\underline{p}$ <.05). The reasons for this result are unclear.

A Phase x Relatedness interaction was found with the nonwords ($\underline{F}$ (1,7) = 9.359, $\underline{p}$ <.018). Mean RTs were significantly faster for 'related' nonwords (618 ms) than for 'unrelated' (664 ms) nonwords in the POST condition.

Other results concerning the primed lexical decision task

Although the previous 4-way ANOVAs on the PRE- and POST- lexical decision word latencies answered questions pertaining to expected patterns of effects in this task, an analysis combining all six factors (6) of the lexical decision task might reveal significant effects that could not otherwise be obtained in the 4-way ANOVA, such as a main effect of Phase. Thus, a six-way analysis of variance was carried out to answer questions pertaining to a) differences between Lists A and B, b) whether RTs were significantly faster in the POST condition than in the PRE, c) whether RTs were faster to related items than to unrelated items, at the short SOA, d) whether RTs were faster to expected items than to unexpected items, at the long SOA and e) whether RTs were faster to trained items than to untrained items. There was one between factor: List (A and B). The five within factors were Phase (PRE and POST), SOA (short and long), Relatedness (related and unrelated), Expectancy (expected and unexpected) and, Training (trained and untrained). The untrained exemplars from a trained category and the untrained category exemplars were collapsed in these analyses. What follows are the significant effects obtained that were not observed in the 4-way ANOVAs.

Phase A main effect of Phase was found indicating that subjects were significantly faster in the POST (602 ms) than in the PRE (735 ms) lexical decision task ($\underline{F}$ (1,6) = 32.797, $\underline{p}$ <.001). A Phase x Training interaction was significant ($\underline{F}$ (1,6) = 14.628, $\underline{p}$ <.01) indicating that subjects were faster on the trained items (566 ms) than on the untrained items (637 ms), in the POST condition. There was no difference between mean RTs in the PRE condition (733 ms for trained and 734 ms for untrained items). A Phase x Relatedness x Expectancy interaction was significant ($\underline{F}$ (1,6) = 10.999, $\underline{p}$ <.02). This interaction arises from a significant decrease in mean RT for the UxR items from the PRE (843 ms) to the POST (635 ms) lexical decision task. Although there was a decrease in the mean RT in the RxR, RxU, and UxU conditions, these were less considerable.

Relatedness There was a main effect of Relatedness indicating that subjects responded significantly faster to related items (628 ms) than to unrelated items (708 ms) ($\underline{F}$ (1,6) = 38.204, $\underline{p}$ <.001). A Phase x Relatedness interaction was significant ($\underline{F}$ (1,6) = 11.367, $\underline{p}$ <.015). RTs were significantly faster to related items (680 ms) than to unrelated items (790 ms) in the PRE condition only.

Training There was a main effect of Training which indicated that trained items were responded to significantly faster than untrained items

(650 ms and 687 ms, respectively) (F (1,6) = 6.506, p <.05). There was a significant List x Relatedness x Expectancy x Training interaction (F (1,6) = 12.615, p <.01). This four-way interaction reveals that the pattern of effects for the untrained-unrelated items, specifically the UxR items, was different across Lists; the mean RT for UxR items in List A (863 ms) was slower than the mean RT to UxR items in List B (641 ms). It should be noted that Phase is collapsed in this interaction and that overall, the mean RT to untrained items was slower than the mean RT to trained items.

It should be noted that the same lexical decision task was given twice prior to training, once with the short SOA and once with the long SOA and the orders were counterbalanced across subjects. Paired t-tests were conducted to compare mean RTs for the first and the second lexical decision task (regardless of SOA and Relatedness) given prior to training. It was found that subjects were already responding significantly faster to words (t (441) = 3.196, p <.001; 735 and 690 ms) and to nonwords (t (444) = 4.790, p <.001; 799 and 738 ms) in the second lexical decision task, prior to training. On the one hand, this would seem to indicate that simply giving the subjects the lexical decision task a second time improves their word recognition speed significantly. On the other hand, subjects may not necessarily be responding more quickly to the items because they recognize them faster, rather RTs could be improving because subjects are becoming more skilled at the task. This repetition effect will be addressed in the discussion.

Discussion

The results from the present study do not support the hypothesis that the primed lexical decision task could detect automatic processing effects resulting from CM training. The results also fail to support the hypothesis of transfer of training (to exemplars from a trained category). The following discussion will focus on each of the questions addressed in the result section.

Does CM training develop automatic processing?

The results from the CM category search task indicated that training was effective in (a) significantly reducing mean RTs to trained and surprise items, as indicated by the negative RT slope, and in (b) marginally improving response accuracy on trained items (items seen 124 times). These results replicate Schneider and Fisk's (1984) CM training results. Although the mean response times for the surprise items decreased significantly, standard deviation did not. This finding could indicate that subjects were not performing a category search after all. Rather they could have memorized the target items. This indirectly supports Logan's (1988) instance theory. Although the evidence in the present study does not make the distinction between direct-memory access and algorithm-based performance, it clearly shows that performance improvement is related to the accumulation of stored instances (124 and 6).

Logan and Stadler (1991) have suggested that changes in performance in the memory search task can be associated with process improvement or process switching mechanisms.

On the one hand, process improvement simply means that the task is carried out the same way except that processing of the task components has become more efficient with practice. On the other hand, process switching mechanisms refer to the development of certain strategies. Three switching mechanisms were identified: item-based learning, category-comparison strategy, and superset strategy. Item-based learning is consistent with Logan's (1988) instance theory, it was also the alternative interpretation provided by Ryan (1983) of his criticisms of Shiffrin and Schneider's (1977) results. The item-based strategy develops with CM training when target responses are retrieved from long-term memory as opposed to being compared to the memory set in short-term memory. In other words, subjects have memorized the targets.

A second process-switching mechanism is the category comparison strategy. This mechanism is consistent with Cheng's (1985) interpretation of the Shiffrin and Schneider (1977) results. In the CM paradigm subjects learn the category from which the targets are selected and simply assess category membership upon target display presentation.

The third switching mechanism is the superset strategy which involves learning a superset of positive items. This strategy is not really applicable to the present design because the superset of positive and negative items were actually from separate categories or 'supersets' and not from within the same category. For example, all 12 exemplars for the category ANIMAL were responded to positively. There was no subset of exemplars from that category that required a negative response.

The data from the surprise trials were used to discourage subjects from memorizing the targets. The design was meant to encourage semantic learning but it may have inadvertently encouraged subjects to develop a category strategy. If this was the case then performance on surprise items should not have been so inconsistent. Although mean RT to surprise items was correlated with training, the standard deviation scores were not. This finding would support an item-based strategy which, according to Logan and Stadler (1991) takes longer to develop than category-based learning. Consequently, if improvement is seen as a decrease in mean RT and stabilizing of RT variance, then only half of this claim is supported by the present data for the surprise items. If subjects were in fact learning the targets then according to Logan and Stadler (1991) improvements in performance would not be associated with automatic processing but rather with the development of strategies, i.e. item-based learning.

The memory set in the present study only contained one item and the display set included three items. All of the targets were semantically related to the prime, they were typical members of the category and they were familiar items. Thus, it is possible that the task was so simple that performance improvement (reduction in RTs) could be associated with process-based learning. This does not necessarily mean that automaticity had developed, perhaps response times were becoming significantly faster as a result of task familiarity. This thesis was not designed to support any particular learning mechanism therefore more than one mechanism can be interpreted as being responsible for performance changes with training.

The training procedure in the present study indicates that performance improvement in the CM design may not actually be related to the development of automaticity. Simple and efficient strategies could have been used by the subject to perform this task. It may also be possible that the number of trials in the present experiment were too few (3534 trials in total) to develop automaticity. Fisk and Schneider (1983) gave their subjects over 11,000 trials of practice even before the training began. Although this might be a plausible explanation for assuming that automaticity failed to develop, Schneider and Fisk (1984) had their subjects complete approximately 4,000 trials in their transfer task; a significant decrease from 11,000 trials . Also Logan and Klapp's (1991) results from an alphabet-arithmetic task reveal that automaticity could develop in a single session and that extended practice may not be necessary after all for developing automaticity. It should be noted that Logan and Klapp's (1991) view of automaticity concerns direct-memory access whereas Schneider and Fisk (1984) view automaticity as a reduction in resources costs. Therefore, caution must be exercised when dealing with the issue of automaticity. Some tasks may require many training trials, while others may require fewer training trials, before performance is noticeably different. It seems that the number of training trials can be a misleading factor in concluding that automaticity has developed.

In order to determine whether automatic processing is acquired through CM training or through any other consistent training procedure automaticity must be directly measured, such as was proposed in the present study. The problem with many tasks is the assumption that they are direct measures of pure automatic processing. The primed lexical decision task is assumed to measure automatic and controlled processing by manipulating SOA, Relatedness, and Expectancy. However, Burke *et al.* (1987) noted that small controlled effects can sometimes be found at the short SOA. Thus, measuring automatic and controlled effects is not always straightforward.

Does the lexical decision task detect the acquisition of automatic net effects produced by CM training? And are these effects detected in a single subject?

The automatic and controlled effects obtained in the PRE condition replicated those obtained by Burke *et al.* (1987). PRE-automatic and controlled net effects were significantly different from zero. However the predicted POST-effects were not observed. If training developed automatic processing then significant differences between PRE- and POST-training should have been, but were not observed. Controlled processing effects, on the other hand, were significantly different in the POST-training for trained words. However, this difference is problematic since the POST-effect itself is not significantly different from zero. Together these results would lead to the conclusion that a) CM training failed to develop automatic processing or b) that the lexical decision task failed to detect differences because subjects were already efficient at word recognition.

The attractiveness of this design is that automatic and controlled processing could be measured for each subject. Individual analyses presented in this research are somewhat compelling because some interesting trends were obtained. Nonetheless, given the reservations concerning the tasks that were used to measure and develop automatic processing, these trends remain inconclusive.

Did transfer of training occur?

Transfer of training did not occur for untrained exemplars from a trained category. Perhaps the present application of Schneider and Fisk's (1984) design was not favourable to transfer. It has been argued that training specific components to automaticity using the CM paradigm leads to specific improvements that do not transfer to other tasks. Logan (1985) has stated that "automatization should result in very specific ways of performing a task, which should provide a rather narrow generalization gradient when transfer to other situations is tested" (p. 378). This raises concerns about whether transfer of training occurs for untrained exemplars from a trained category, or whether training transfers to an entirely different task.

As Schneider and Fisk demonstrated transfer occurred in the same type of task in which the exemplars were trained. Thus, it is reasonable to speculate that transfer did not occur in the present study because the lexical decision task demands were different from those in the training procedure. Also according to Logan's (1988) instance theory transfer of training should not occur because 'automaticity' relies on the accumulation of instances. Since the untrained exemplars were only seen a fraction of the time that trained items were seen, the accumulation of instances for untrained exemplars was unequal. Thus, these results would support Logan and Stadler's (1991) hypothesized item-based learning mechanism.

Primed Lexical Decision Task

The pattern of results that are usually found in a primed lexical decision task were not replicated in the present study. Due to a genuine confounding variable of repetition it seems that training might not have been a contributing factor in the changes measured in the POST-condition.

The confounding variable in the primed lexical decision task was item repetition. This repetition effect refers to response facilitation (repetition priming) for items that have previously appeared on the target list (Durgunoglu, 1988). Results in the present study revealed that prior to training subjects had already improved their performance on words and nonwords in all conditions (significantly faster RTs) in the second lexical decision task (collapsing across SOA, prime-target relatedness, and expectancy conditions). It could be argued that repetition priming, in addition to semantic priming, was in part responsible for any of the observed response facilitation effects obtained in the lexical decision task. However, further analyses, reported below, indicate that there was no interaction between semantic priming conditions and task repetition (where items were repeated across tasks).

The primed lexical decision task was given to each subject four times; once at each SOA prior to and after training. Two separate three-way ANOVAs (one on word RT and one on nonword RT) were conducted with 2 between factors; lexical decision task Repetition (1 to 4) and SOA (short and long) and 1 within factor; Semantic Priming Condition - RxR, UxR, UxU, RxU.

No main effect of Repetition was found (p >.05) for words. There was a Semantic Priming Condition main effect in that the RxR trial RTs were fastest and the UxR trial RTs were slowest. The Semantic Priming x Repetition interaction was not significant (p >.05). A non-significant interaction would support the claim that facilitation in the POST condition (for automatic processing) was due to training rather than repetition of words in the lexical decision task.

These results support den Heyer, Goring, and Dannenbring (1985) findings that semantic priming and repetition are additive factors (Sternberg, 1969). The additive relationship was further supported by den Heyer (1986) and Durgunoglu (1988). To explain the non significant interaction it was suggested that semantic priming and word repetition effects occur at different stages of information processing as long as the lag between repetitions is more than 7 intervening trials (Den Heyer & Benson, 1988).

The lexical decision task in the present study differs from the above study in that item repetition never occurred within a task, only across tasks. In addition, prior to training, subjects completed the short and long SOA lexical decision tasks on separate days, and within at least 30 minutes of each other in the post-training phase. Given that the lag between repetitions was long enough it can be assumed that the semantic and repetition facilitation effects were additive.

To summarize, the results from the lexical decision task are problematic since the usual pattern of effects were not observed either in the PRE- or the POST-lexical decision tasks.

Conclusion

The results from the present research have led to the following questions: Is consistent training necessary to develop automatic processing? Is the lexical decision task a valid measure of automatic and controlled processing? What is a good measure for evaluating changes in automatic and controlled processing following training?

In the semantic category search task the 'to be trained' exemplars were already well known and were in effect 'pre-trained'. Also, the pool of transfer items was rather small (a single item per category). Perhaps training methods should manipulate information that subjects already know (words) in novel ways in order to eliminate the 'pre-trained' effect. For example, the 'rule' in the present design was to locate a semantically related target. If the rules required subjects to process words in a novel way then the development of automatic processing could be more strictly monitored. For example, subjects could learn to associate polygons with exemplars from specific categories. When the polygons can be correctly identified as exemplars, then priming could be measured by presenting the category in which the 'polygon' belongs (see MacLeod & Dunbar, 1988). Also, the pool of words used for training could be increased so that they are not easily memorized. Further research could also vary the number of consistent mapping trials for a particular rule to assess the number of trials needed to produce a significant change in automatic and controlled net effects. This type of training has been implemented by Kramer, Strayer and Buckley (1990) in a rule-based memory search task and by MacLeod and Dunbar (1990) in a modified Stroop-like task. These studies could indicate whether CM training develops automaticity or efficient strategies.

As noted in the introduction, the lexical decision task has been criticized as a valid measure of word recognition (Balota & Chumbley, 1984; Seidenberg *et al*, 1984). Although the present study did not attempt to verify these criticisms it is possible that the problem with the lexical decision task is that it is not an accurate measure of automatic and controlled processing in word recognition. Recently Jacoby (1991) has offered an alternative approach to the issue of measuring automatic and controlled processing. Rather than assuming that task performance is a direct reflection of either automatic or controlled processes, he advances that task performance reflects a blend of both types of processes. Jacoby's process dissociation method measures the unique contribution of both automatic and controlled processes within a task.

The idea of combining both the category search task and the lexical decision task was thought to be a novel way of measuring automatic processing of word recognition skills following training. It was also a method for measuring changes in individual performance ($\underline{n} = 1$). The fact that the results did not support the hypotheses does not invalidate this approach. In order to claim that automaticity has been trained, research should focus on the resulting changes on a PRE and POST task that measures automatic and controlled processing. Perhaps the old approach of trying to obtain pure measures of automaticity should be revised.

References

Anderson, J.R. (1982). Acquisition of cognitive skill. *Psychological Review, 89(4)*, 369-406.

Antos, S.J. (1979). Processing facilitation in a lexcical decision task. *Journal of Experimental Psychology: Human Perception and Performance, 5*, 527-545.

Balota, D.A., & Chumbley, J.I. (1984). Are lexical decisions a good measure of lexical access? The role of word frequency in the neglected decision stage. *Journal of Experimental Psychology: Human Perception and Performance, 10(3)*, 340-357.

Battig, W., & Montague, W. (1969). Category norms for verbal items in 56 categories: A replication and extension of the Connecticut category norms. *Journal of Experimental Psychology Monograph, 80*, 1-46.

Becker, C.A. (1985). What do we really know about semantic context effects during reading? In D. Besner, T.G. Waller, G.E. MacKinnon (Eds.), *Reading Research: Advances in Theory and Practice, Volume 5*. New York: Academic Press.

Becker, C.A. (1980). Semantic context effects in visual word recognition. An analysis of semantic strategies. *Memory and Cognition, 8(6)*, 493-512.

Becker, C.A. (1979). Semantic context effects and word frequency effects in visual word recognition. *Journal of Experimental Psychology: Human Perception and Performance, 5(2)*, 252-259.

Burke, D.M., White, H., & Diaz, D.L. (1987). Semantic priming in young and older adults: Evidence for age constancy in automatic and attentional processes. *Journal of Experimental Psychology: Human Perception and Performance, 13(1)*, 79-88.

Cheng, P. (1985). Restructuring versus automaticity: Alternative accounts of skill acquisition. *Psychological Review, 92(3)*, 414-423.

Chumbley, J.T., & Balota, D.A. (1984). A word's meaning affects the decision in lexical decision. *Memory and Cognition, 12(6)*, 590-606.

Collins, A., & Loftus, E. (1975). A spreading activation theory of semantic processing. *Psychological Review, 82(6)*, 407-428.

Coltheart, M., Davelaar, E., Jonasson, J.T., & Besner, D. (1981). Access to the internal lexicon. In J.R. Anderson (Ed.), *Cognitive Skills and their Acquisition*. Hillsdale, NJ: Erlbaum.

Crossman, E.R. (1959). A theory of the acquisition of speed-skill. *Ergonomics, 2*, 153-166.

de Groot, A.M., Thomassen, A.J., & Hudson, P.T. (1982). Associative facilitation of word recognition as measured from a neutral prime. *Memory and Cognition, 10*, 358-370.

den Heyer, K. (1986). Manipulating attention-induced priming in a lexical decision task by means of repeated prime-target presentations. *Journal of Memory and Language, 25*, 19-42.

den Heyer, K., & Benson, K. (1988). Constraints on the additive relationship between semantic priming and word repetition and on the interactive relationship between semantic priming and stimulus clarity. *Canadian Journal of Psychology, 42(4)*, 399-413.

den Heyer, K., Goring, A., & Dannenbring, G.L. (1985). Semantic priming and word repetition: The two effects are additive. *Journal of Memory and Language, 24*, 699-716.

den Heyer, K., Goring, A., Gorgichuk, S., Richards, L., & Landry, M. (1988). Are lexical decisions a good measure of lexical access? Repetition blocking suggests the affirmative. *Canadian Journal of Psychology, 42(3)*, 274-296.

Durgunoglu, A.Y. (1988). Repetition, semantic priming and stimulus quality: Implications for the interactive-compensatory reading model. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14(4)*, 590-603.

Favreau, M., & Segalowitz, N. (1983). Automatic and controlled processes in the first- and second-language reading of fluent bilinguals. *Memory and Cognition, 11(6)*, 565-574.

Favreau, M., & Segalowitz, N. (1980). Semantic category norms for the English and French Quebec populations. Paper presented at the 41st meeting of the Canadian Psychological Association. Calgary, Alberta.

Fisk, A.D., & Schneider, W. (1983). Category and word search: Generalizing search principles to complex processing. *Journal of Experimental*

Psychology: Learning, Memory, and Cognition, *9*, 177-195.

Frederiksen, J.R., Warren, B.M., & Rosebery, A.S. (1985a). A componential approach to training reading skills: Part I. Perceptual units training. *Cognition and Instruction*, *2(2)*, 91-130.

Frederiksen, J.R., Warren, B.M., & Rosebery, A.S. (1985b). A componential approach to training reading skills: Part II. Decoding and use of context. *Cognition and Instruction*, *2(3&4)*, 271-338.

Graesser, A.C., Hoffman, N.L., & Clark, L.F. (1980). Structural components of reading time. *Journal of Verbal Learning and Verbal Behavior*, *19*, 135-151.

Hasher, L. & Zacks, R.T. (1979). Automatic and effortful processes in memory. *Journal of Experimental Psychology: General*, *108(3)*, 356-388.

Hirst, W., Spelke, E.S., Reaves, C.C., Caharack, G., & Neisser U. (1980). Dividing attention without alternation or automaticity. *Journal of Experimental Psychology: General*, *109(1)*, 98-117.

Jacoby, L.L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory and Language*, *30(5)*, 513-541.

Jonides, J., & Mack, R. (1984). On the cost and benefit of cost and benefit. *Psychological Bulletin*, *96(1)*, 29-44.

Kahneman, D. (1973). *Attention and Effort*. Englewood Cliffs, NJ: Prentice-Hall.

Klapp, S., Boches, C.A., Trabert, M.L., & Logan, G. (1991). Automatizing alphabet-arithmetic: II. Are there practice effects after automaticity is achieved? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *17(2)*, 196-209.

Kramer, A.F., Strayer, D.L., & Buckley, J. (1990). Development and transfer of automatic processing. *Journal of Experimental Psychology: Human Perception and Performance*, *16(3)*, 505-522.

LaBerge, D., & Samuels, S.J. (1974). Toward a theory of automatic information processing in reading. *Cognitive Psychology*, *6*, 293-323.

Logan, G. (1990). Repetition priming and automaticity: Common underlying mechanisms? *Cognitive Psychology, 22*, 1-35.

Logan, G. (1988). Toward an instance theory of automatization. *Psychological Review, 95(4)*, 492-527.

Logan, G. (1985a). Skill and automaticity: Relations, implications, and future directions. *Canadian Journal of Psychology, 39(2)*, 367-386.

Logan, G., & Klapp, S. (1991). Automatizing alphabet-arithmetic: I. Is extended practice necessary to produce automaticity? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 17(2)*, 179-195.

Logan, G., & Stadler, M. (1991). Mechanisms of performance improvement in consistent mapping memory search: Automaticity or strategy shift? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 17(3)*, 478-496.

Lorch, R.F., Balota, D.A., & Stamm, E.G. (1986). Locus of inhibition effects in the priming of lexical decisions: Pre- or post-lexical access? *Memory and Cognition, 14(2)*, 95-103.

MacKay, D.G. (1982). The prolem of flexiility, fluency, and speed-accuracy trade-off in skilled behavior. *Psychological Review, 89*, 483-506.

MacLeod, C., & Dunbar, K. (1988). Training and Stroop-like interference: Evidence for a continuum of automaticity. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14(1)*, 126-135.

Morton, J. (1979). Facilitation in word recognition: Experiments causing change in the logogen model. In P.A. Kolers, M. Wrolstad, & H. Bouma (Eds.), *Processing of Visible Language*. New York: Plenum Press.

Morton, J. (1969). Interaction of information in word recognition. *Psychological Review, 76*, 165-178.

Neely, J. (1990). Semantic priming effects in visual word recognition: A selective review of current findings and theories. In D. Besner, & G. Humphreys (Eds.), *Basic Processes in Reading: Visual Word Recognition*, (pp. 263-336). Hillsdale, NJ: Erlbaum.

Neely, J. (1977). Semantic priming and retrieval from lexical memory: Roles of inhibitionless spreading activation and limited-capacity attention. *Journal of Experimental Psychology: General, 106*, 226-254.

Neely, J. (1976). Semantic priming and retrieval from lexical memory: Evidence for facilitatory and inhibitory processes. *Memory and Cognition, 4(5)*, 648-654.

Newell, A., & Rosenbloom, P.S. (1981). Mechanisms of skill acquisition and the law of practice. In J.R. Anderson (Ed.), *Cognitive Skills and their Acquisition*. Hillsdale, NJ: Erlbaum.

Norris, D. (1986). Word recognition: Context effects without priming. *Cognition, 22*, 93-136.

Paap, K.R. & Ogden, W.C. (1981). Letter encoding is an obligatory but capacity-demanding operation. *Journal of Experimental Psychology: Human Perception and Performance, 7(3)*, 518-527.

Perfetti, C.A. (1985). *Reading Ability*. New York: Oxford University Press.

Posner, M.I., & Snyder, C.R. (1975b). Attention and cognitive control. In R. Solso (Ed.), *Information Processing and Cognition*. Hillsdale, NJ: Erlbaum.

Rabbitt, P. & Banerji, N. (1989). How does very prolonged practice improve decision speed? *Journal of Experimental Psychology: General, 118(4)*, 338-345.

Ratcliff, R., & McKoon, G. (1988). A retrieval theory of priming in memory. *Psychological Review, 95(3)*, 385-408.

Ryan, C. (1983). Reassessing the automaticity-control distinctions: Item recognition as a paradigm case. *Psychological Review, 90(2)*, 171-178.

Schneider, W. (1985). Toward a model of attention and the devlopment of automatic processing. In M.I. Posner & O.S. Marin (Eds.), *Attention and Performance XI*. (Pp. 475-492). Hillsdale, NJ: Erlbaum.

Schneider, W., & Fisk, A.D. (1984). Automatic category search and its transfer. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 10*, 1-15.

Schneider, W., & Fisk, A.D. (1982b). Concurrent automatic and controlled visual search: Can processing occur without resource cost? *Journal of*

Experimental Psychology: Learning, Memory, and Cognition, *8*, 261-278.

Schneider, W., & Fisk, A.D. (1982c). Degree of consistent training: Improvements in search performance and automatic process development. *Perception and Psychophysics*, *31(2)*, 160-168.

Schneider, W., & Shiffrin, R.M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, *84(1)*, 1-66.

Seidenberg, M.S., & McClelland, J.L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review*, *96(4)*, 523-568.

Seidenberg, M.S., Waters, G.S., Sanders, M., & Langer, P. (1984). Pre- and post-lexical loci of contextual effects on word recognition. *Memory and Cognition*, *12(4)*, 315-328.

Shiffrin, R.M., & Schneider, W. (1977). Controlled and automatic human information processing: II. Perceptual learning, automatic attending, and a general theory. *Psychological Review*, *84(2)*, 127-190.

Stanovich, K.E. (1991). Word recognition: Changing perspectives. In R. Barr, M.L. Kamil, P. Mosenthal, and P.D. Pearson (Eds.), *Handbook of Reading Research, Volume 2*. New York: Academic Press.

Stanovich, K.E. (1980). Toward an interactive-compensatory model of individual differences in the development of reading. *Reading Research Quarterly*, *16*, 32-71.

Stanovich, K.E., & West, R.F. (1981). The effect of sentence context on ongoing word recognition: Tests of a two-process theory. *Journal of Experimental Psychology: Human Perception and Performance*, *7(3)*, 658-672.

Sternberg, S. (1969). The discovery of processing stages: Extension of Donder's method. *Acta Psychologica*, *30*, 276-315.

Strayer, D.L., & Kramer, A.F. (1990). Attentional requirements of automatic and controlled processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *16(1)*, 67-82.

Zbrodoff, J.N., & Logan, G. (1986). On the autonomy of mental processes: A case study of arithmetic. *Journal of Experimental Psychology: General, 115(2)*, 118-130.

Appendix A

List of targets

Instructions and list of targets in the memory and lexical decision tasks

Below is a list of words, some of which will be presented to you in this experiment. If you do not know the meaning of any one of these words, please do not hesitate to ask. It is important for your task that you know the meaning of each of the following words.

apple
apricot
ash
asparagus
axe
balsam
banana
baseball
basketball
bean
bear
beaver
beech
beet
birch
broccoli
cabbage
carrot
cat
cedar
celery
cherry
chisel
climbing
corn
cow
cypress
daisy
deer
diving
dog
dogwood
donkey
dress
drill
elm
fencing
fishing
football
fox
garlic
goat
golf
grape
grapefruit
grinder
hammer
hemlock
hiking
hockey
hoe
horse
knife
lathe
leek
lemon
level
lily
lime
lion
mango
maple
melon
mouse
mushroom
oak
onion
palm
pants
peach
pear
peas
pick
pig
pine
pineapple
pliers
plum
poplar
potato
prune
rabbit
raccoon
radish
rake
redwood
running
sailing
sander
saw
scissors
screws
sheep
shirt
shovel
skating
skiing
soccer
spinach
spruce
strawberry
swimming
sycamore
tangerine
tennis
tiger
tomato
tulip
turnip
watermelon
willow
wolf
wrench
wrestling

Appendix B

Memory Task Stimuli

SERIES A		SERIES B	
CATEGORY	TARGETS	CATEGORY	TARGETS
ANIMAL	beaver donkey raccoon sheep wolf	SPORT	baseball basketball climbing football wrestling
FRUIT	grapefruit pineapple strawberry tangerine watermelon	VEGETABLE	asparagus broccoli garlic leek mushroom
TOOL	grinder level sander scissors screws	TOOL	grinder level sander scissors screws
TREE	hemlock cypress dogwood palm sycamore	TREE	hemlock cypress dogwood palm sycamore

Appendix C

Lexical Decision Task Stimuli

SERIES A		SERIES B	
CATEGORY	TARGETS	CATEGORY	TARGETS
ANIMAL	bear-blar	SPORT	diving-duving
	cat-dat		fencing-mencing
	cow-gow		fishing-lishing
	deer-deet		golf-goaf
	dog-doy		hiking-hizing
	fox-fod		hockey-wockey
	goat-loat		running-rinning
	horse-horpe		sailing-sairing
	lion-rion		skating-shating
	mouse-couse		skiing-skoing
	pig-pag		soccer-soucer
	rabbit-mabbit		swimming-saimming
	tiger-tiver		tennis-ternis
FRUIT	apple-ipple	VEGETABLE	bean-blan
	apricot-aprilot		beet-beeb
	banana-balana		cabbage-cabbare
	cherry-clerry		carrot-cabrot
	grape-trape		celery-celerp
	lemon-vemon		corn-carn
	lime-lome		onion-inion
	mango-margo		peas-pras
	melon-melor		potato-zotato
	peach-peath		radish-gadish
	pear-peam		spinach-stinach
	plum-plim		tomato-yomato
	prune-prine		turnip-jurnip

Lexical Decision Task Stimuli (continued)

SERIES A		SERIES B	
CATEGORY	TARGETS	CATEGORY	TARGETS
TOOL	axe-ixe	TOOL	axe-ixe
	chisel-chipel		chisel-chipel
	drill-drull		drill-drull
	hammer-haymer		hammer-haymer
	hoe-koe		hoe-koe
	knife-knire		knife-knire
	lathe-rathe		lathe-rathe
	pick-pice		pick-pice
	pliers-pleers		pliers-pleers
	rake-ruke		rake-ruke
	saw-saz		saw-saz
	shovel-scovel		shovel-scovel
	wrench-brench		wrench-brench
TREE	ash-osh	TREE	ash-osh
	balsam-palsam		balsam-palsam
	beech-geech		beech-geech
	birch-firch		birch-firch
	cedar-cudar		cedar-cudar
	elm-ilm		elm-ilm
	maple-eaple		maple-eaple
	oak-onk		oak-onk
	pine-bine		pine-bine
	poplar-poolar		poplar-poolar
	redwood-remwood		redwood-remwood
	spruce-sprice		spruce-sprice
	willow-sillow		willow-sillow
CLOTHING*	dress-druss	CLOTHING*	dress-druss
	pants-panks		pants-panks
	shirt-phirt		shirt-phirt
FLOWER*	daisy-paisy	FLOWER*	daisy-paisy
	lily-lity		lily-lity
	tulip-turip		tulip-turip

*These category names never appeared as primes and only the exemplars were used in the UxR conditions.

Appendix D

Training Stimuli

SERIES A		SERIES B	
CATEGORY	TARGETS	CATEGORY	TARGETS
ANIMAL	bear	FLOWER	daisy
	cat		iris
	cow		lilac
	dog		lily
	horse		orchid
	lion		pansy
	tiger		tulip
CLOTHING	coat	FRUIT	apple
	dress		banana
	pants		cherry
	shirt		grape
	shoe		peach
	skirt		pear
	socks		plum
SPORT	diving	TREE	birch
	golf		elm
	hiking		maple
	hockey		oak
	skiing		pine
	soccer		spruce
	tennis		willow
TOOL	axe	VEGETABLE	bean
	chisel		carrot
	drill		celery
	hammer		corn
	pliers		peas
	shovel		potato
	wrench		tomato

Training Stimuli (continued)

DISTRACTORS

(DRINK)	beer	(METAL)	brass
	coffee		bronze
	coke		chrome
	gin		copper
	juice		gold
	milk		iron
	rum		lead
	rye		nickel
	scotch		ore
	soda		pewter
	tea		silver
	vodka		steel
	water		tin
	wine		zinc
(DWELLING)	cabin	(BODY)	arm
	castle		brain
	cave		ear
	dorm		eye
	duplex		face
	flat		foot
	home		hand
	hotel		head
	house		heart
	hut		leg
	igloo		mouth
	motel		neck
	shack		nose
	tent		torso

Training Stimuli (continued)

DISTRACTORS

(FABRIC)	cloth cotton dacron denim fur linen nylon rayon satin silk suede tweed velvet wool	(VEHICLE)	bike boat buggy bus car cart jeep ship subway taxi train truck van wagon
(FURNITURE)	bed bench buffet chair couch desk lamp piano shelf sofa stereo stool stove table	(WEAPON)	arrow bomb cannon chain club gun pistol rifle rope spear stick sword tank whip

Appendix E

Training Targets

SERIES A

CATEGORY	TARGET	SURPRISE
ANIMAL	bear	deer
	cat	fox
	cow	mouse
	dog	pig
	horse	rabbit
	lion	
	tiger	
CLOTHING	coat	blouse
	dress	hat
	pants	jeans
	shirt	slacks
	shoe	suit
	skirt	
	socks	
SPORT	diving	fencing
	golf	fishing
	hiking	running
	hockey	sailing
	skiing	skating
	soccer	
	tennis	
TOOL	axe	hoe
	chisel	knife
	drill	lathe
	hammer	rake
	pliers	scissors
	shovel	
	wrench	

Training Stimuli (continued)
SERIES B

CATEGORY	TARGET	SURPRISE
FLOWER	daisy	aster
	iris	azalea
	lilac	begonia
	lily	dahlia
	orchid	peony
	pansy	
	tulip	
FRUIT	apple	apricot
	banana	lemon
	cherry	lime
	grape	melon
	peach	prune
	pear	
	plum	
TREE	birch	balsam
	elm	cedar
	maple	hemlock
	oak	poplar
	pine	redwood
	spruce	
	willow	
VEGETABLE	bean	beet
	carrot	cabbage
	celery	onion
	corn	spinach
	peas	turnip
	potato	
	tomato	

Appendix F

Tables of Automatic and Controlled Processing Net Effects

Table F-1

Automatic and Controlled Processing Net Effects in ms for Trained Items as a function of n = 1 resulting from the Burke *et al.* (1987) formula

Subjects		Net Effect (in ms) Automatic	Controlled
		Trained items	
AB			
	Pre	54	84
	Post	137	15
DW			
	Pre	124	137
	Post	109	-47
JD			
	Pre	106	100
	Post	129	-16
JG			
	Pre	217	-43
	Post	147	-196

Table F-1 (continued)

Automatic and Controlled Processing Net Effects in ms for Trained Items as a function of n = 1 resulting from the Burke *et al.* (1987) formula

		Net Effect (in ms)	
Subjects		Automatic	Controlled
		Trained items	
JM			
	Pre	-99	121
	Post	103	3
MC			
	Pre	153	304
	Post	102	-14
MM			
	Pre	161	113
	Post	89	39
SG			
	Pre	133	1
	Post	-72	-42

Table F-2

Automatic and Controlled Processing Net Effects in ms for Untrained Items as a function of n = 1 resulting from the Burke *et al.* (1987) formula

		Net Effect (in ms)	
Subjects		Automatic	Controlled
		Untrained items	
AB			
	Pre	-3	40
	Post	116	-10
DW			
	Pre	240	1
	Post	-65	25
JD			
	Pre	53	-46
	Post	22	-41
JG			
	Pre	74	-146
	Post	-34	-186

Table F-2 (continued)

Automatic and Controlled Processing Net Effects in ms for Untrained Items as a function of n = 1 resulting from the Burke *et al.* (1987) formula

		Net Effect (in ms)	
Subjects		Automatic	Controlled
		Untrained items	
JM			
	Pre	142	76
	Post	-89	128
MC			
	Pre	124	545
	Post	242	288
MM			
	Pre	139	33
	Post	35	-60
SG			
	Pre	112	-32
	Post	72	128

Appendix G

Training Figures

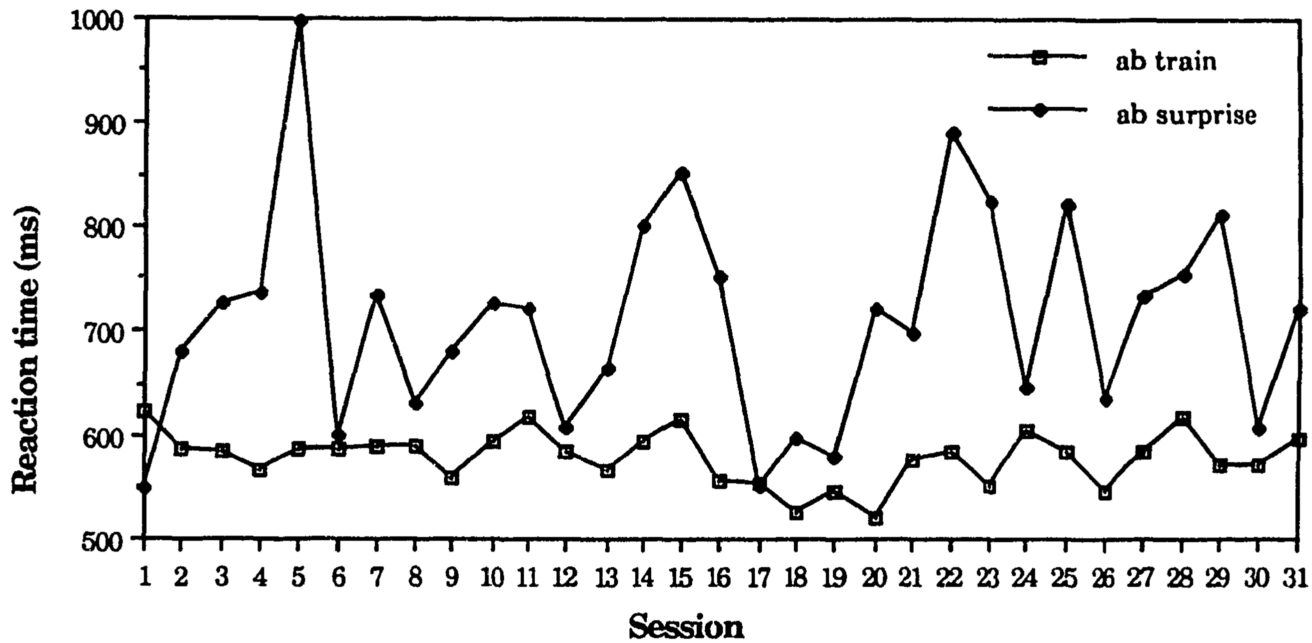


Figure G-1 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject AB.

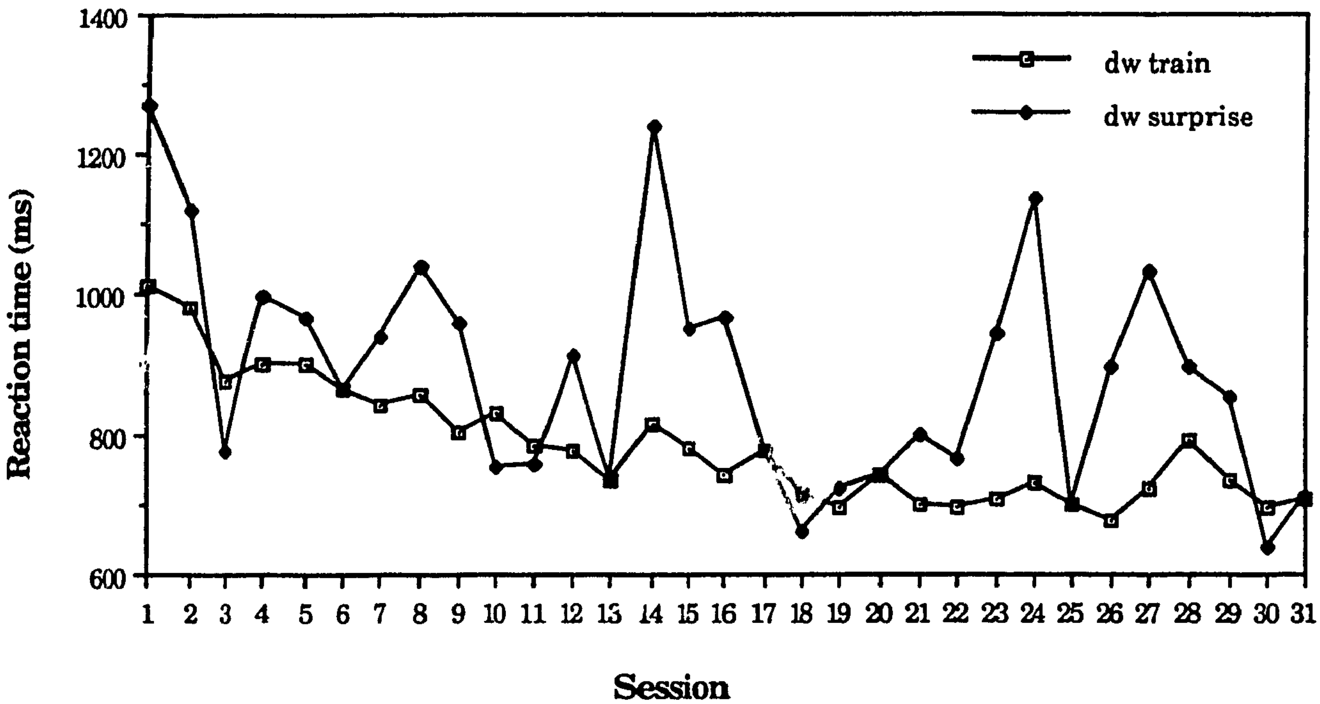


Figure G-2 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject DW.

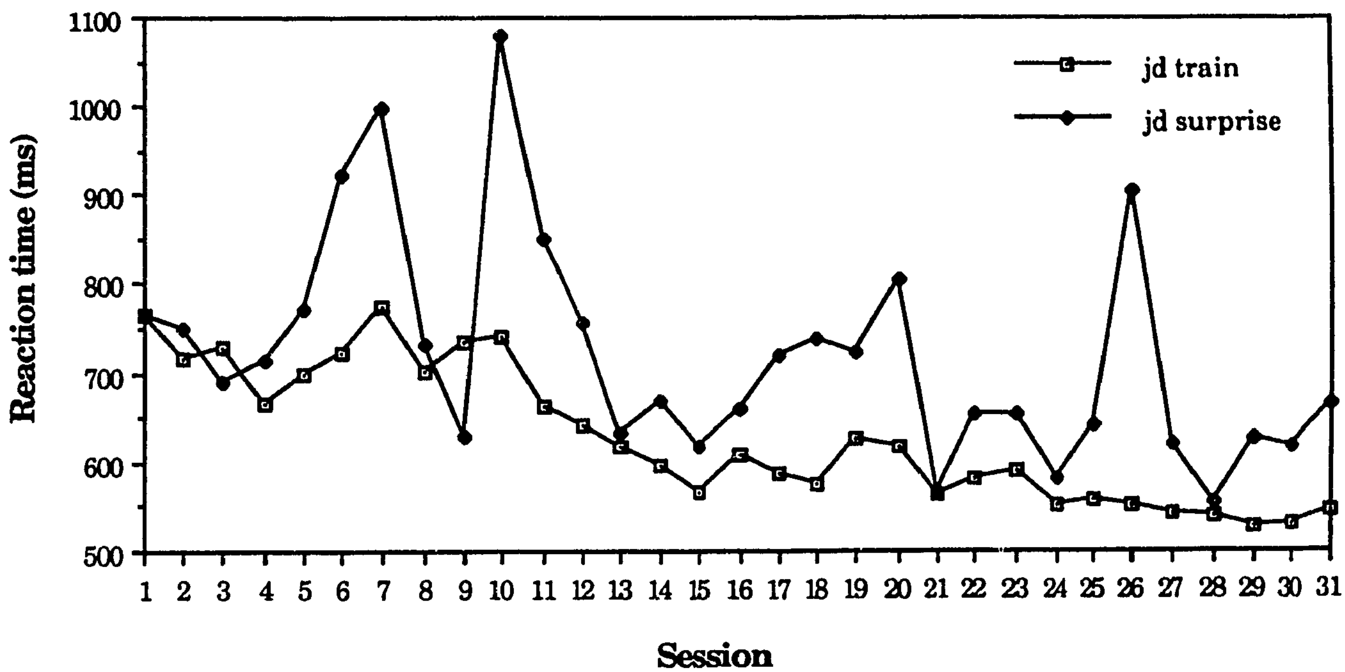


Figure G-3 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject JD.

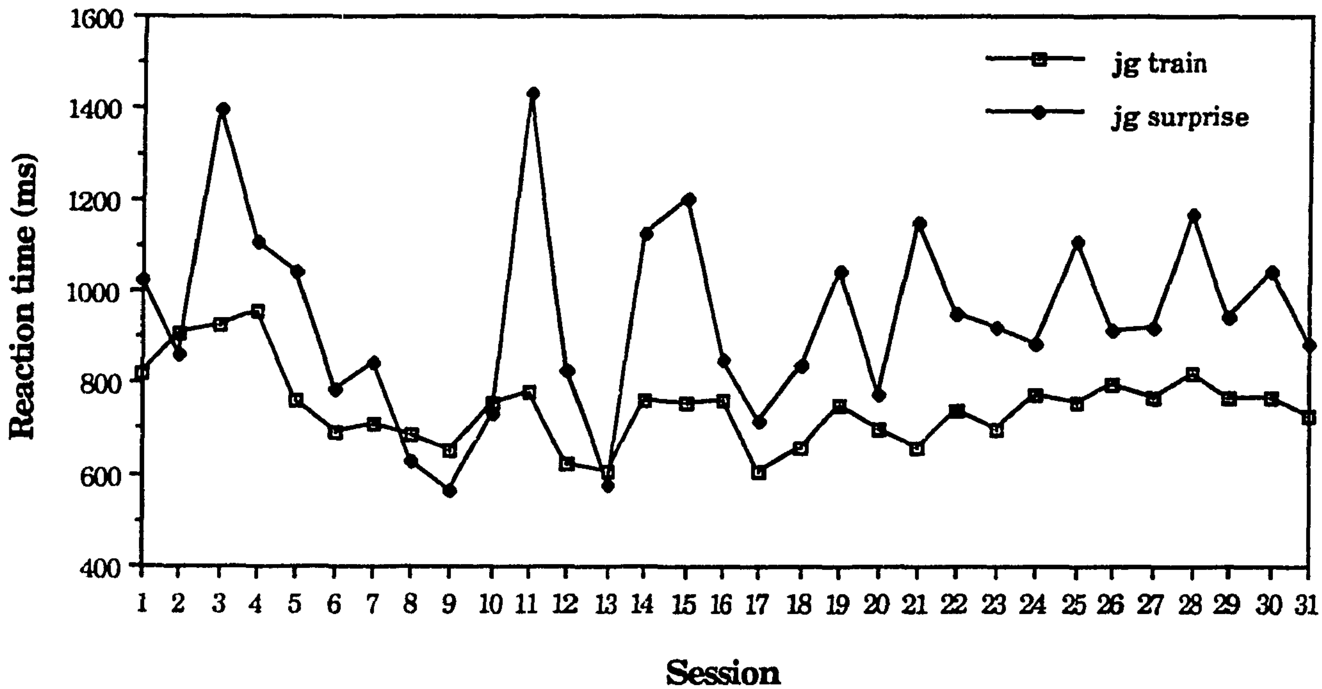


Figure G-4 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject JG.

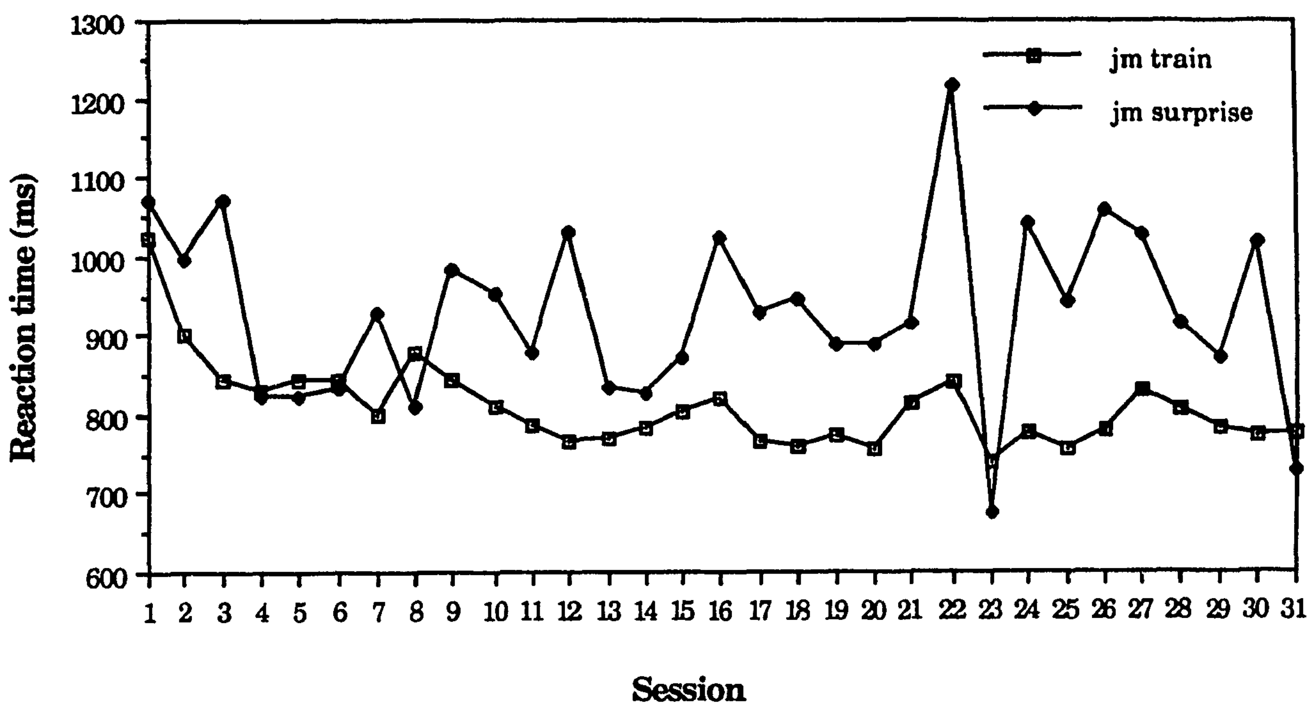


Figure G-5 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject JM.

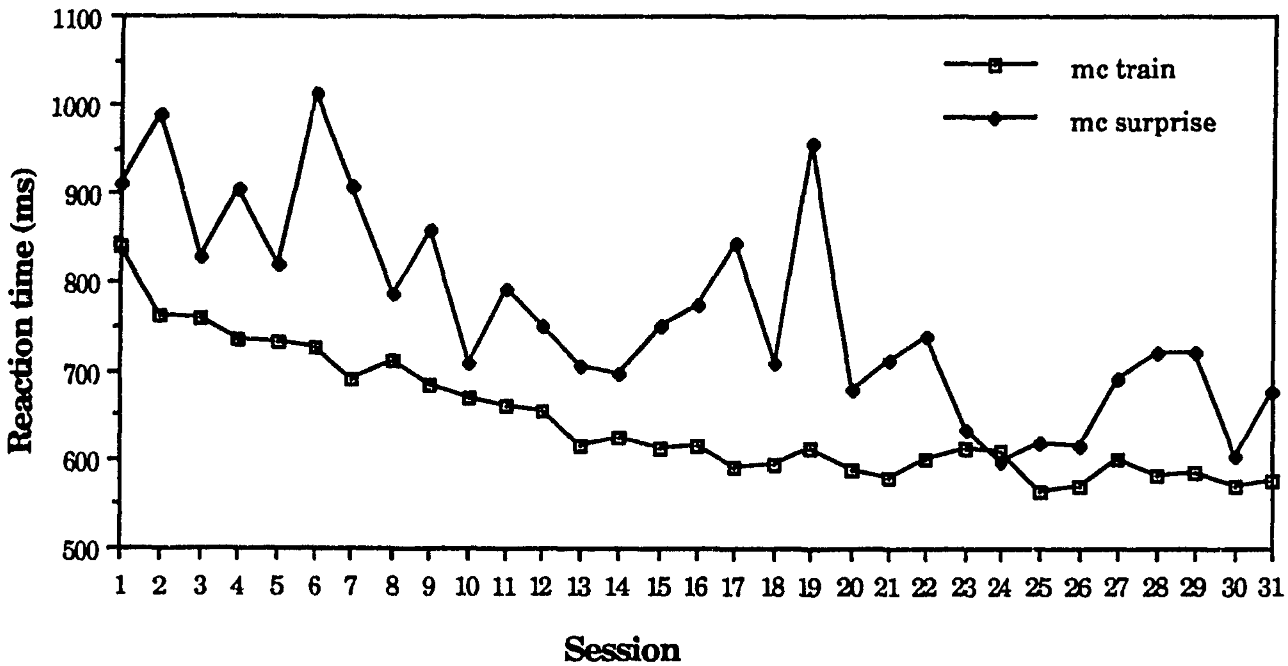


Figure G-6 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject MC.

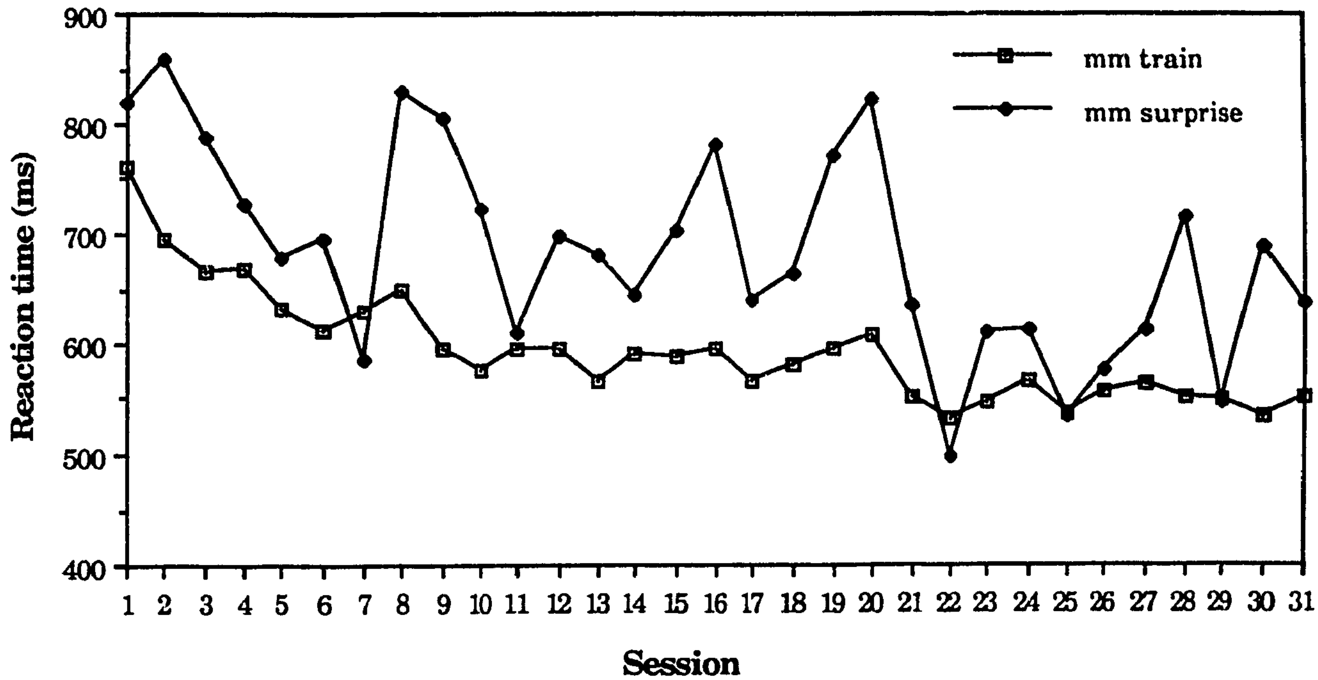


Figure G-7 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject MM.

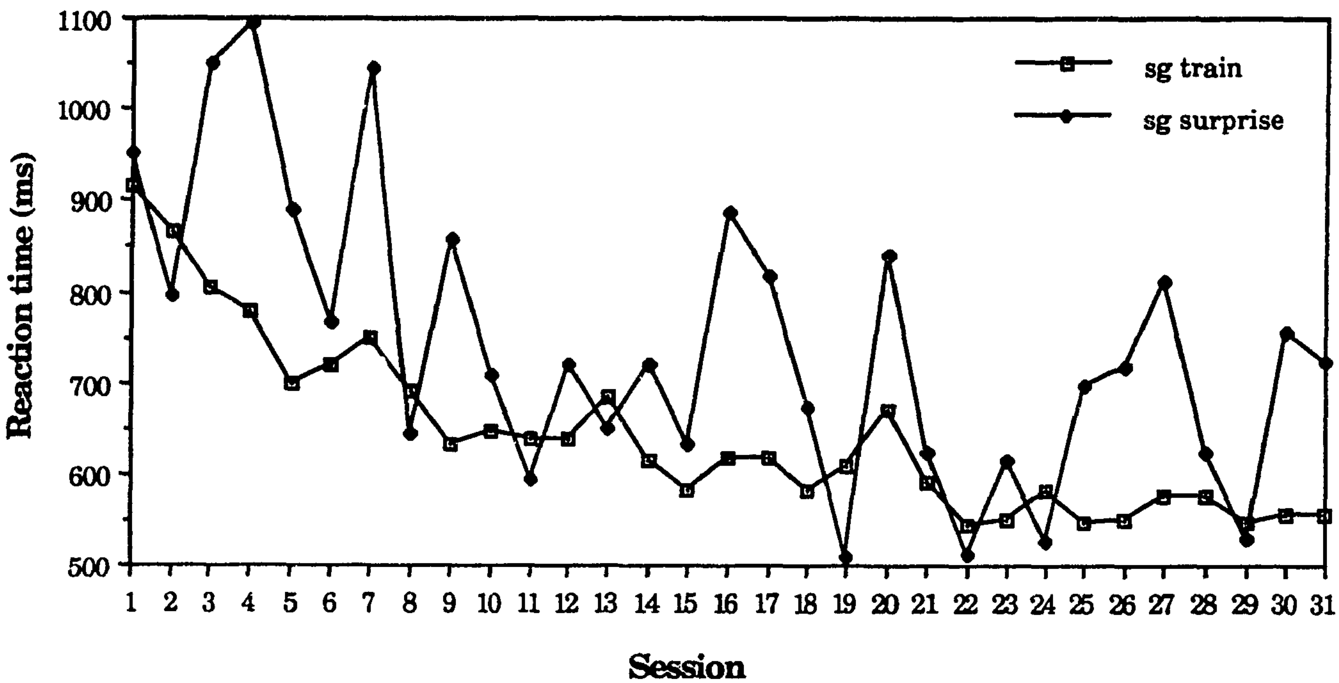


Figure G-8 Mean reaction time (ms) per session as a function of training for surprise and trained items in the category search task for subject SG.