Brain Electrical Activity and Automatization

Thesis for Masters by Research
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Declaration

This thesis contains no material which has been accepted for the award of any other degree at any other University, and to the best of my knowledge and belief contains no material previously published or written by another person, except where due reference is made.

Christopher Anthony Hocking
March, 1999
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Abstract

Novices and experts show distinct differences in the performance of many tasks. Experts may perform a task quickly and accurately with seemingly little attention or effort, whilst novices will perform the same task more slowly and with great effort. The transition from novice to expert performance occurs only after extended practice and has been conceptualized as a transition from controlled to automatic processing, and has been modeled as a reduction in attention or cognitive resources. Alternatively, based on findings relating to learning in the domain of number arithmetic, it has also been modeled as a transition from an algorithmic, or computationally-based process, to the use of memory retrieval.

However, relatively few studies have investigated the changes in brain activity associated with such a transition. In this study, the Steady-State Probe Topography technique was used to investigate differences in the topography of the Steady-State Visual Evoked Potential (SSVEP) between an unpracticed and a well-practiced analogue of number arithmetic, Alphabet arithmetic.

Subjects showed decreases in response time with practice that followed a power law and were suggestive of automatization. During initial, unpracticed performance of the task, processing of the Alphabet Arithmetic equations was characterised by increased SSVEP amplitude and decreased latency in frontal regions, whilst after extended practice, performance was characterised by reduced SSVEP amplitude and increased latency. It is suggested that the frontal activity during the initial, unpracticed stage of the task implicates a role for working memory, whilst the amplitude decrease and latency increase observed in the well-practiced task may reflect a reduction in excitation, consistent with ideas of an improvement in brain efficiency, and possibly an increase in inhibitory processes.
Chapter 1

Introduction

One of the quantitative effects of practice for perceptual-motor tasks is an increase in speed of performance which follows a power law describing logarithmic gains in performance speed as the number of trials increases, even at very high levels of skill and after extended practice (Newell & Rosenbloom, 1981). This power law appears to apply to practice learning of all kinds, including cognitive tasks (Newell & Rosenbloom, 1981).

An increase in performance speed is not the only change that occurs with practice. James (1890) noted that practice led to the development of habitful behaviours that required little conscious attention, and that these habits were involved in, and important to, a large proportion of everyday life.

This idea of a reduction in attention with practice, and a transition from conscious, attention-demanding processing to automatic, attentionally-independent processing has been instantiated within the framework of automatic and controlled modes of information processing (Shiffrin & Schneider, 1977; Posner & Snyder, 1975). Controlled processing is slow and requires attention and effort, whilst automatic processing is fast and effortless, and does not require attention. This view of human information processing, as a dichotomy between controlled and automatic processes, led to a renewal of psychological interest in the topic of learning as a function of practice (Adams, 1987).

However, a number of shortcomings of this approach have led to the development of memory theories of automatization as an alternative (see Logan, 1985). This approach is similar to studies of expert and novice performance differences in that it is a knowledge-based approach to learning and skill development (Shuell, 1990), and assumes that the development of automaticity reflects a build-up of information in memory, and a transition from computationally-based processing to memory-retrieval.

One particular model, instance theory (Logan, 1988a), suggests that automatization involves a race between a computational process or algorithm, and direct memory-retrieval (Logan, 1988a). This approach closely parallels conceptions...
of the development of skilled simple arithmetic performance, in which a counting strategy is gradually replaced by memory retrieval (Groen & Parkman, 1972). Developmental observations that younger children utilize a counting strategy in simple arithmetic, whilst older children primarily use memory retrieval (Siegler, 1988; Miller, Perlmutter & Keating, 1984; Koshmider & Ashcraft, 1991) confirm memory retrieval approaches to the automatization of simple arithmetic.

Similarly, a task that is an analogue of simple arithmetic (alphabet arithmetic) shows evidence of a transition from counting to remembering. Speed of performance increases with practice according to a power law, and subjects report decreased use of counting strategies and increased use of memory recall with increasing practice (Logan, 1988a). Evidence of a transition from counting to remembering in alphabet arithmetic suggests that this task mimics the theoretical processes that underlie performance of numerical arithmetic, and may therefore be useful in assessing the validity of accounts based on counting and memory processes in number arithmetic (Zbrodoff, 1995).

It has been suggested that investigations of cognitive processing in arithmetic may shed considerable light on the mental operations and knowledge representations of mathematics (Koshmider & Ashcraft, 1991). Also, research suggests that arithmetic knowledge may be represented in a similar form to that suggested for word knowledge (in a semantic network accessed by automatic spreading activation), and so the study of arithmetic memory retrieval processes may also contribute to the understanding of skill development and automatization in other domains (LeFevre, Bisanz & Mirkonjic, 1987).

However, strictly behavioural/computational approaches are now out-dated (Carr, 1992). The development of neural imaging technologies, which has allowed for the measurement of brain activity during performance of cognitive tasks, and the relatively recent emergence of cognitive neuroscience, suggests that the utilization of neuroscientific approaches may be a way of providing converging evidence for issues of attention and automaticity (Carr, 1992).

Nevertheless, in terms of neurophysiological approaches to automatization, there have been only a small number of studies investigating changes in brain activity associated with extended practice. Few studies have investigated changes in brain activity with practice on arithmetic tasks (Pauli et al., 1994; 1996), and to the authors'
knowledge, no studies of brain activity associated with performance of an alphabet arithmetic task have previously been carried out.

Therefore, the aim of this thesis was to utilize the Steady-State Probe Topography technique to investigate changes in brain electrical activity associated with automatization of an alphabet arithmetic task.

To achieve this aim, the literature review will examine the quantitative and qualitative changes in behaviour that occur with practice, and the two main theoretical approaches to automatization - resource theories and memory theories, and review the small number of neurophysiological studies that have addressed the development of automaticity with practice for certain cognitive tasks, including simple arithmetic.

The third chapter will introduce the reader to transient evoked potentials and probe evoked potential methodology, before moving on to steady-state evoked responses, particularly the steady-state visual evoked potential and its utilization in the steady-state probe topography (SSPT) technique. A short review of SSPT findings will be made to familiarize the reader with interpretations of SSPT data in relation to brain activity prior to the formation of the hypothesis for this study.

The method chapter will give detailed information relating to the contents and structure of the alphabet arithmetic task, the task presentation procedure, the method of evoking the SSVEP, and the electroencephalographic recording technique. This chapter will also provide details of the analysis of the SSPT data, including artifact detection, calculation of the amplitude and phase components of the SSVEP, data ‘smoothing’, averaging of data about task events (i.e., stimulus presentation, response and feedback), cross-subject pooled data averaging, and topographic and statistical parametric mapping.

The results chapter will highlight the main findings of the study in terms of changes in behavioural measures (response time and accuracy) with practice, changes in SSVEP amplitude and phase with practice, and amplitude and phase differences between early, unpracticed alphabet arithmetic and later, well-practiced alphabet arithmetic.

The discussion will tie in the major findings of this study to other experimental findings in the literature relating to automatization, particularly those dealing with practice effects and automatization of arithmetic tasks (since alphabet arithmetic is an analogue of simple arithmetic), and consideration will be given to the role of working memory in arithmetic.
Chapter 2

Automaticity

The focus of this review will be how automatization develops with extended practice in cognitive domains. An overview of some of the learning literature relating to skill development in both the cognitive and perceptual-motor domains will be provided in order to highlight the importance of automatic processes as hierarchically-organized components of skills.

In Section 2.1, some conceptualizations of the stages involved in skill development, or the path from novice to expert performance, will be outlined, and a short review of early conceptions of habitful or automatic behaviour will be made, as well as a review of the role of automaticity in skilled performance.

A clarification of the term 'automaticity' will be made in Section 2.2, in order to differentiate “pre-attentive automaticity” in the realm of sensory processing from the focus of this thesis on automaticity that occurs post-attentively and develops from extended practice with cognitive tasks and motor activities (Logan, 1992).

Qualitative and quantitative differences in performance between individuals with high levels of skill for a given domain (experts) and those with low levels of skill (novices) will be examined in Sections 2.3 & 2.4. Quantitative measures of the development of skill and automaticity have shown that speed of performance increases with repetition of a task according to a power law, and models that have been proposed to account for this law will be discussed in Section 2.4.

A consideration of modern, human information processing approaches to learning and skill development will be made in Section 2.5, starting with the dichotomy between automatic and controlled modes of processing, and leading on to resource theories (which view the development of automaticity as reflecting a reduction in the utilization of finite cognitive resources). This section will conclude with an examination of the problems with the two-process view of automaticity, which encompasses resource theories and the dichotomy between controlled and automatic processing modes.
Section 2.6 will review the more recent, alternative approach (memory theory), which views automatization as reflecting the development of memory-retrieval processes. This approach regards automaticity as a continuous dimension, rather than a dichotomy, and appears to be a superior framework from which to conceptualize automatization.

Section 2.7 will examine the nature of arithmetic processing, including the storage and inter-associations of arithmetic facts in memory, and the differences between expert and novice arithmetic performance.

Finally, a review of the limited neurophysiological work on changes in brain activity associated with practice will be made, with a mind to identifying regions of the cortex implicated in novice and expert performance. Experimental studies investigating regions of the cortex implicated in arithmetic processing at novice and expert stages of learning will also be considered (Section 2.8).

2.1 Learning, skill development and automaticity

2.1.1 Phases of learning and skill development

From a biological point of view, learning can be defined as “a process in which the responses of the organism are modified as a result of experience” (p.1055, Curtis & Barnes, 1989), and such a broad definition will also serve as a starting point in examining the cognitive processes of learning and automatization in humans.

The fact that experience can alter the responses of an organism is “one of the pervasive characteristics of behaviour” (Adams, 1987) and is evident from the noticeable performance improvements associated with practice (Snoddy, 1926; Crossman, 1959) and differences between novice and expert performance (Chi, Glaser & Rees, 1982). In this review (following Shuell, 1990), the term novice will be taken to refer to someone with little experience or practice in a given domain (as distinct from no practice), whilst an expert will be considered to be someone with extensive experience and practice.

The existence of identifiable differences between experts and novices is usually interpreted as implying that learning involves a progression through a number of distinct phases that can be differentiated from one another (i.e. Fitts, 1964, Anderson, 1982, Shuell, 1990).
Shuell (1990) proposed a speculative general description of the phases of learning. In the initial phase, the learner will encounter a large number of facts which are conceptually isolated. Whereas an expert may see the relationships between the information, the novice will not and will only be able to memorize facts and use pre-existing schema to interpret and organize those facts. The information acquired during this stage will be tied to the context in which it is experienced, and processing will be of a global nature because general domain-independent strategies must be used, since no schema that is specific to the new learning domain yet exists.

In the intermediate phase, the learner will begin to see the relationships between the information encountered and will be able to apply acquired information across varying situations and not just within the context in which the information was acquired.

In the terminal phase, knowledge structures or schemata become more integrated and autonomous, the learner will use domain-specific strategies and emphasize efficiency and speed of performance rather than concentrating on learning. Any learning that does occur will consist either of the addition of new facts to schemata or the formation of higher level schemata consisting of a number of sub-schemata.

A three-phase model of perceptual-motor skill learning was proposed by Fitts (1964; Fitts & Posner, 1967). In the early phase, the learner begins to understand the task and its demands, begins to integrate responses and develops an executive program to control subroutines and provide a framework for decision-making. In the intermediate (associative) phase, the formation of specific stimulus-response associations occurs, subroutines are tried out and changed as errors are eliminated. In the last phase, skills become increasingly autonomous and less subject to interference from other activities or environmental distractions.

In both of these descriptions, performance in the early or initial stages corresponds to novice performance, when the task is novel to the learner and little practice has occurred. Novice performance is slow and error prone, and effort and attention are required for each minor movement or decision (Schneider, Dumais & Shiffrin, 1984). The final phases proposed encompass expert performance, with the learner having experienced a large amount of practice such that little attention is required to carry out long sequences of action or thought, and performance becomes fast and accurate (Schneider, Dumais & Shiffrin, 1984). After sufficient practice, an
expert will have "so thoroughly mastered the procedures and heuristics in their area of expertise that the manipulation of these operations is virtually automatic and requires little conscious effort for implementation" (Sternberg, 1995). At this stage, task performance can be considered to be automatic. Importantly, continuing practice can improve performance, such that even those considered to be experts may enhance their already superior performance (see Klapp, Boches, Trabert & Logan, 1991; Crossman, 1959).

2.1.2 Habit and automaticity

James (1890) examined the differences between effortful, novice performance and the automatic nature of the performance of experts in his discussion on the formation of habit.

James (1890) identified two results of the formation of habit, the first being that habit “simplifies the movements required to achieve a given result, makes them more accurate and diminishes fatigue” (James, 1890, p.73). This phenomenon was made clear by Henry Maudsley (p.155 “Physiology of Mind”; cited in James, 1890, p.74) in the following passage; “If an act became no easier after being done several times, if the careful direction of consciousness were necessary to its accomplishment on each occasion, it is evident that the whole activity of a lifetime might be confined to one or two deeds - that no progress could take place in development. A man might be occupied all day in dressing and undressing himself; the attitude of his body would absorb all his attention and energy; the washing of his hands or the fastening of a button would be as difficult to him on each occasion as to the child on its first trial; and he would furthermore be completely exhausted by his exertions”.

The second observation was that “habit diminishes the conscious attention with which our acts are performed” (James, 1890, p.74). This is evident when one examines the routine manner in which we perform many daily activities, and the fact that we are often only aware or conscious of such a process when it is interrupted by a need to change the action in some way, such as when an object has been moved from its expected location (James, 1890). These are movements of which we are quite unaware of the details; for example, which shoe or sock is put on first when dressing. We dress without giving any conscious attention to this and yet cannot give an answer.
to the question without first mentally rehearsing the act or even actually performing or miming it (James, 1890).

In making these observations, James (1890) was one of the first to allude to the concept of automatization of actions, in that he saw practice and learning as being associated with a shift from the conscious allocation of attention to automatic processing requiring minimal attention (Adams, 1987).

In more modern times, the idea of reduced attentional involvement in well-practiced, skilled or expert performance has been one of the main core defining characteristics of an automatic process (Schneider & Shiffrin, 1977; LaBerge & Samuels, 1974; Posner & Snyder, 1975; see Norman, 1981). Reduced attentional involvement in automatic or expert performance is evident from observed reductions in dual-task interference with practice (Schneider & Fisk, 1982; Fisk & Schneider, 1983; Logan, 1979; Hirst, Spelke, Reaves, Caharack & Neisser, 1980), and is also evident in the fact that automatic processes tend to be unavailable to conscious awareness. This is manifested in slips or lapses in the performance of everyday, familiar activities, such as forgetting how many spoonfuls of coffee you have placed in the pot or switching on a light when leaving a room during the daytime (Reason, 1984; see also Norman, 1981).

2.1.3 Similarities between skill and automaticity

Besides the property of reduced attentional involvement, other characteristics of automatic processes that are similar to characteristics of skilled or expert performance (see Schneider, Dumais & Shiffrin, 1984; Shiffrin & Dumais, 1981) are that automatic processing is fast (Posner & Snyder, 1975; Schneider, Dumais & Shiffrin, 1984), effortless (Schneider & Shiffrin, 1977; Logan, 1979), and relatively autonomous (Posner & Snyder, 1975; Shiffrin & Schneider, 1977; Zbrodoff & Logan, 1986). Automaticity and skill appear to be similar in other ways, including the fact that practice plays an important part in producing skill (Logan, 1985) and extended practice has been tied to the development of automaticity (Newell & Rosenbloom, 1981). Another similarity between the two phenomenon is that there appears to be no limit to skill development (Crossman, 1959) nor automatization (Klapp, Boches, Trabert & Logan, 1991).
Furthermore, whilst the differences between experts and novices would seem to suggest a sharp divide between skilled and unskilled performance (Logan, 1985), closer inspection suggests that skill is a continuum. The term skill usually refers to performance of a complex task, and a task can be defined as “a set of goals which a person tries to attain, and a set of constraints to which the person must adapt in order to obtain the goals” (p.368, Logan, 1985). Those who can obtain the goals and adapt better to the constraints of the task are more skilled than those who cannot. The fact that both skill and automaticity can be acquired through practice and that skill is a relative continuum suggests that automaticity should also be viewed as a continuum (Logan, 1985).

2.1.4 Differentiating automaticity and skill - components versus whole tasks

Although automaticity and skill appear to share similar properties and are closely related, they have been consistently differentiated from one another. For example, in the motor-skills domain, automaticity is viewed as an important aspect of skill development (Logan, 1985) and a necessary component of skill.

The first exponents of this view were Bryan & Harter (1899), who suggested that higher-level skills could not be attained before lower-level skills were automatized. Bryan & Harter (1899) noted that as learning progressed, letters, then words, and eventually whole sentences could be recognized and remembered, and suggested that learning involved a “hierarchy of habits”, whereby over a period of time, behaviour was organized into larger and more complex functional units. Integral to this hierarchy was the automation of the components or sub-skills of a task. The apparent occurrence of plateaus in the learning curve as subjects moved from understanding letters to words, and words to sentences, led Bryan and Harter (1899) to interpret the plateaus as a time at which lower-order habits were almost completely developed but were not yet automatic enough to permit the development of higher-order habits.

The idea of discrete, hierarchical processes which develop over time and with practice was also emphasized by Fitts (1964), who noted that even a young child already possesses a large number of highly organized general and specific skills involved in walking, maintenance of posture, object manipulation and language. Each of these skills is assumed to consist of a high order executive program and a myriad of lower order subroutines, which may also be shared with other high order skills. By the
time adulthood is reached, hundreds of identifiable skills exist, such that learning a completely new skill will be very rare (Fitts, 1964).

Such a conception of human cognition and control of actions is a computer metaphor and has perhaps been the most influential development relating to hierarchical organization and control of skills (Fitts, 1964). Human control systems are viewed as operating in an analogous way to computer programs, whereby lower order programs (sub-routines) which carry out very simple functions are ‘called up’ by higher order programs or executive routines (see Miller, Galanter & Pribram, 1960) and central to this concept is the existence of discrete ‘subskills’ or pre-formed motor programs (Stelmach, 1976) or action systems (Shallice, 1972). The concept of hierarchical organization of skills is an integral part of most modern conceptions of skill learning (Fitts, 1964; Newell & Rosenbloom, 1981; MacKay, 1982; Anderson, 1982).

Similarly, under the human information processing approach to skill learning and automaticity, LaBerge & Samuels (1974) suggested that automatization of component skills was necessary to avoid exceeding the attentional capacity of the information processing system. Importantly, this view of skilled performance as consisting of component automatic processes suggests that the rate of skill acquisition is dependent on the rate of automatization of these component processes (Logan, 1988a). For example, reading does not become fluent until visual decoding of letters and comprehension of word meaning are automatized (LaBerge & Samuels, 1974).

Such approaches to automaticity view automatic processes as components that can be thought of as specialists, and which are responsible for different aspects of performance within the overall skill (Logan, 1985). Performance of a complex task involves the coordination of a number of component processes within a short period of time in order to achieve a goal, and the more complex the task, the greater the number of different components that will be recruited (Logan, 1985).

Given this conceptualization of automaticity, Logan (1985) contends that rather than referring to entire tasks as the term skill does, the term automaticity refers to the properties of certain types of tasks that are fast, effortless and show autonomy (p.368), and therefore is most appropriate when discussing the components of a task. This also agrees with Jonides, Naveh-Benjamin & Palmer (1985) who suggest that the concept of automaticity is “best applied to components of complex behaviours rather than to behaviours as a whole” (p.158). Also, most modern treatments of automaticity
Automaticity (e.g. LaBerge & Samuels, 1974; Schneider, Dumais & Shiffrin, 1984; Shiffrin & Dumais, 1981) focus on components of tasks rather than tasks as wholes (p.368, Logan, 1985).

The closeness of the relation between automaticity and skill makes it difficult to delineate the two phenomena empirically. However, an experiment showing that six facts could be remembered after fifteen minutes of practice just as well as 40 facts could be remembered after twelve hours of practice led Logan & Klapp (1991) to suggest that automaticity refers to the memorability of facts in a particular domain whilst "skill refers to the proportion of the domain that is automatized" (p.194). Relating this back to the study, the subjects who learned 40 facts were more skilled than those who learned six facts, but their performance was not more automatic.

This result implies that automaticity can be developed within a short period of time, but skill development may be different - it may depend upon the domain. If facts in a domain are highly interactive (unlike arithmetic, where the facts are largely independent of one another), such complex hierarchical organization may only be appreciated “when a substantial proportion of the domain is mastered” (p.194, Logan & Klapp, 1991), and as such, extensive practice of the whole domain would be necessary.

Such a distinction highlights a contrast between breadth and depth of knowledge (Logan & Klapp, 1991). It also concurs with the view of automatic processes as components of skills (LaBerge & Samuels, 1974; Schneider, Dumais & Shiffrin, 1984; Shiffrin & Dumais, 1981; Jonides, Naveh-Benjamin & Palmer, 1985; Logan, 1985) and as such is a useful way of differentiating between skill and automaticity.

2.2 Relationship between pre-attentive processing and automaticity

Whilst one of the main properties of an automatic process is that they demand little attention, this has led to confusion between pre-attentive processing and automaticity, since pre-attentive processes can also be thought of as components of skilled behaviour. This has arisen from the long history of research on early versus late selection which interpreted “evidence that processing is automatic as evidence that processing is preattentive” (p.319, Logan, 1992).
Pre-attentive processes are involved in sensory perception, are driven by stimulus presentation, and occur independently of attention (Logan, 1992). They are the most fundamental forms of automatic processes (Naataanen, 1992) and are considered to be pre-attentive in that they occur temporally prior to being intentionally attended (Logan, 1992). Examples of pre-attentive processes include the processing of basic stimulus features such as colour, form, and orientation in vision (Treisman & Gelade, 1980); the transfer of sensory information to sensory memory (Neisser, 1967; Cowan, 1984, 1988); and processes leading to an attention switch, such as physical changes in an unattended auditory channel during dichotic listening (Cherry, 1953), and movements in the peripheral visual field which automatically switch attention to, and cause foveation of, the stimulus (Jonides, 1981). These are biologically significant mechanisms which provide information regardless of where attention may be directed, when such information is potentially most important to us, at onset or offset, or when a change occurs (Naataanen, 1992).

The two-process view of automaticity considers that automatic processing and pre-attentive processing are the same, since both are seen as occurring independently of attention (Logan, 1992), leading some researchers to suggest that a process may become preattentive through learning (Shiffrin & Schneider, 1977; Schneider, 1985).

However, research suggests that processes cannot be made preattentive through training. Treisman & Gelade (1980) found that automatization of search for a conjunction of visual stimulus features did not occur, whilst more recently, Treisman, Vieira & Hayes (1992) showed that whilst automatic processing of spatial relations between features in a display could be developed with practice, automatization did not create new features that could then themselves be pre-attentively detected.

Logan (1992) suggests that pre-attentive processes provide the information upon which attentional selection is based and therefore are distinct from automatic processes developed through extended practice. Neumann (1984) also argues that pre-attentive or ‘bottom-up’ processes should not be considered “to be the prototypes of automatic processes” (p.284).

This will be the position taken in this thesis, and this review will focus on processing that is made automatic through extended practice, processes that initially require concentration and effort, but through repetition are able to be performed quickly and effortlessly, and with less attention than was initially required.
2.3 Learning is not just automaticity

Whilst for skilled performers the components of skills can be considered to be 'more automatic' than for unskilled performers, skilled or expert performance is not just more automatic than novice performance (Logan, 1985). It is apparent that learning involves automaticity or the formation of habit (James, 1891), but it also includes other changes, such as the acquisition and integration of declarative and procedural knowledge relating to a specific domain (Chi, Glaser & Rees, 1982).

For example, a number of studies have shown superiority of expert memory. DeGroot (1966) found that chess masters were able to recall the positions of nearly all the pieces on the board after a five second exposure to a complex middle-game position, whereas novices could only recall a few of the pieces. Similarly, Egan & Schwartz (1979) found that when reconstructing symbolic drawings of circuit diagrams, experts showed better recall of circuit diagrams than novices following five, ten or fifteen second exposures of the diagrams. Chase & Simon (1973) found that whilst both chess masters and novices recalled piece positions in chunks (groups of pieces related to each other in some manner), the masters chunks typically contained three to six pieces whilst the novices chunks contained only single pieces. However, recall superiority of skilled technicians and master chess players did not hold for randomly arranged symbols (Egan & Schwartz, 1979) and random, non-real chess board positions (Chase & Simon, 1973) respectively, suggesting that the function and inter-relation of items is more important for experts (Chi, Glaser & Rees, 1982).

Differences in the organization of memory for novices and experts have also been found. Egan & Schwartz (1979) found that skilled technicians grouped together functional units such as filters and amplifiers, whereas novices produced chunks based on the proximity of the various elements in the diagram. Physics experts knowledge tends to be organized around fundamental physics principles whilst that of novices is organized around the literal components of the problem (Chi, Glaser & Rees, 1982). Expert physicists also show shorter pause times between retrieval of successive physics equations, suggesting that the equations are stored together in chunks which allow for rapid activation of other related equations (Larkin, 1979).

Qualitative performance changes with practice are evident from the fact that experts perform tasks differently to novices (Logan, 1985), using different approaches
and strategies (Chi, Glaser & Rees, 1982). Expert physicists show a four-fold decrease in solution times compared to novices and use different solution paths (Simon & Simon, 1978). Experts tend to “work forward”, using the variables given in the problem to generate equations that can be solved using the available information, whereas novices tend to “work backward”, starting with an equation which contains the unknown variable (Simon & Simon, 1978).

Chi, Glaser & Rees (1982) suggest that the difficulties faced by novices in problem-solving are mainly due to inadequate procedural knowledge which prevents them from inferring further information from the cues explicitly given in the problem, even though their schemata contain sufficient declarative knowledge about the problem. In contrast, experts tend to necessarily generate such quality inferences.

Overall, skilled performers tend to have more declarative knowledge about their area of expertise than novices, and also a better understanding of their own capabilities and the strategies available to them (Logan, 1985). They show superior memory (and organization of that memory), as well as a greater ability to deduce implicit patterns and relations between objects from explicit cues (Chi, Glaser & Rees, 1982).

2.4 Quantitative changes with practice (the power law of practice)

The automatization of skills and the effects of practice have been the subject of much speculation in the study of human behaviour, dating back to the writings of James (1890), and the work of Bryan & Harter (1899) and Snoddy (1926). Early investigations of skill learning focused on improvement in performance with continuing practice (measured as reductions in performance time and error rates) for the operation of workplace machinery (Bryan & Harter, 1899; de Jong, 1957; Crossman, 1959). For such manual skills, speed of performance was the primary criteria by which an individuals skill level was measured, and it was found to increase gradually and continuously with practice (Crossman, 1959). Both Crossman (1959) and de Jong (1957) showed that speed of performance increased linearly when the log of performance time was plotted against the log of number of repetitions of the skill. Similar results have also been confirmed in other studies of perceptual-motor skill learning (Snoddy, 1926) and development of motor responses (Card, English & Burr,
suggested that there exists a consistent relationship between practice and speed of performance (Newell & Rosenbloom, 1981).

Figure 2.1 The power law of practice as indicated by data from Crossman (1959) on cigar-making (A), mirror-tracing (Snoddy, 1926 – replotted in Newell & Rosenbloom, 1981) (B), a version of the card game solitaire (Newell & Rosenbloom, 1981) (C), and Kolers' (1975) study of reading inverted text (D). N.B. Kolers (1975) data plots time taken to read a page of text in minutes vs. number of pages already read, with each 0.3 increment representing a doubling of the value on each scale (i.e., 0.6 on the y-axis represents 2 minutes and 2.1 on the x-axis represents 128 pages of text).

Just as it is clear that this law of practice is so ubiquitous in perceptual-motor learning, it is equally clear that it is also apparent in psychological behaviour, including perception (Kolers, 1975) (Figure 2.1d), decision-making (Seibel, 1963), and problem-solving (Newell & Rosenbloom, 1981) (Figure 2.1c). It is readily apparent that, given that all tasks require some cognition, this law of practice cannot easily be attributed to only one aspect of task performance (i.e., improvement of the motor skill component) (Newell & Rosenbloom, 1981). The occurrence of the log-log or power law of practice is so widespread as to be suggestive of the existence of a
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common law of learning, one that is dependent upon “quite general features of the learning situation or of the system that learns” (Newell & Rosenbloom, 1981, p.16).

However, the continuous nature of the speed-practice relationship leads to difficulties in identifying the stages of skill development that are thought to occur with continuing practice (e.g., Fitts, 1964; Shuell, 1990).

Bryan & Harter (1899) found evidence of plateaus for telegraph operators receiving Morse code and inferred them as evidence of the existence of identifiable and differentiable stages of skill development, but there is little empirical evidence suggesting that periods of non-improvement are experienced during learning (Adams, 1987). Keller (1958) maintains that such effects may instead be due to artifacts such as the lack of opportunity to improve, or a lack of motivation. Keller (1958) suggests that this explanation is supported by the rapid improvement following plateaus shown by Bryan & Harter’s (1899) subjects, and that the improvements were due to the transfer to a task which required an information transmission rate higher than previous work. Additionally, the validity of plateaus is questionable as Bryan & Harter’s (1899) findings have not been replicated and evidence of plateaus in motor learning curves is scarce (Adams, 1987).

Indeed, it is evident that even after practice periods lasting years and millions of trials or repetitions, plateaus in learning are not reflected in measures of performance time. The data on cigar-manufacturing (Crossman, 1959) indicates that learning was still occurring after extensive practice and that a leveling out of learning is more likely to be due to external factors (in this case the cycling time of the machine) than to the reaching of a true limit of learning (Crossman, 1959).

Speed of performance data fitted by the law of practice shows a relatively smooth and continuous improvement in performance as a function of the number of repetitions, with a concomitant decrease in the rate at which that learning occurs. Most models of learning suggest that learning is continuous, and occurs without plateaus or periods during which improvement ceases (Crossman, 1959; Fitts, 1964; Shuell, 1990; Newell & Rosenbloom, 1981; Anderson, 1982).

Although a number of theories utilize the concept of phases or stages (Fitts, 1964; Shuell, 1990; Anderson, 1982), this merely serves as a tool in understanding the changes that occur with learning, and is probably more a reflection on the difficulties of identifying and quantifying skill characteristics at various points on a continuous
learning curve, rather than the fact that stages can be differentiated from one another on the basis of performance measures such as reaction time (Fitts, 1964).

It seems then that the development of both skill and automaticity follow the power law of practice (see Crossman, 1959; Snoddy, 1926; Newell & Rosenbloom, 1981; Logan, 1988a; Klapp & Logan, 1991), which is logical given the importance of practice in their development (see Logan, 1985).

2.4.1 Models of Learning and the Power Law

Crossman (1959) was the first to attempt to propose a model accounting for the power law (Newell & Rosenbloom, 1981), suggesting that the learner possesses a repertoire of different methods, each with a given probability of being selected, which may be used to accomplish the task. Practice serves to increase the probability of selection of faster, more efficient methods, at the expense of slow or unsuccessful methods, perhaps using the least amount of cognitive work or “physiological cost” to the learner as the criterion for the selection of a given method. Another mechanism of selection suggested by Crossman (1959) is the decay of short-term memory, whereby feedback from faster responses would arrive more quickly than from slower responses, leaving less time for decay of the memory for that particular method, and thereby enhancing the chances of that method being used again.

MacKay (1982), in looking at production of speech, proposed a model consisting of a hierarchical system of interconnected nodes in which the rate of learning for a given node is determined by prior practice. Different nodes will have different improvement rates due to differing amounts of practice; unpracticed nodes will show rapid improvement whilst extensively practiced nodes will show little improvement. The overall rate of learning is a product of the distribution of these learning rates across the hierarchy and is initially very fast because the unpracticed nodes dominate the hierarchy. Later, the overall learning rate slows because only slowly improving, practiced nodes are left to make a contribution.

Anderson (1982) proposed a theory of cognitive skill acquisition composed of three stages which correspond to the three stages proposed by Fitts (1964). It is based on the Adaptive Control of Thought (ACT) production system (Anderson, 1976), in which declarative knowledge about a domain is represented as a network of propositions (nodes) which are interconnected. As learning occurs, this declarative
knowledge is converted into procedural knowledge concerned with how to perform a
task or solve a problem. According to this model, learning involves the encoding of
facts in an unanalyzed form (Declarative stage), the combination of declarative
knowledge into procedures (Knowledge compilation) and the tuning of procedural
knowledge so that it might be applied more efficiently and appropriately (Procedural
stage). In this model, the speed-up in performance is due to a power function decrease
in the number of productions (large numbers of small productions are collapsed into a
smaller number of larger productions), and ACT’s strengthening process, which leads
to a power function increase in the rate at which productions are applied.

Another mechanism proposed to explain the power law is based on the
principle of exhaustion (Newell & Rosenbloom, 1981). Learning is considered to
consist of finding and incorporating improvements to the current method of learning,
and as a person learns, information becomes organized into larger and more complex
structures or chunks. General purpose improvements are applicable across a wide
range of conditions, but as learning progresses, the span of the chunk and the
information it encompasses increases and the chunk becomes more complex, such that
it can be applied to a smaller number of more specialized conditions. In other words,
the number of situations in which the chunk can be applied is gradually “exhausted”,
leading to a decrease in the learning rate (Newell & Rosenbloom, 1981).

The power law is evident in virtually all learning situations involving
extended practice (Newell & Rosenbloom, 1981) and can be thought of as a 'universal
descriptor' of skill acquisition that any model of skill acquisition and automaticity
must be able to account for (Logan, 1988a).

2.5 Resources and automatic versus controlled processing

Early information-processing approaches conceived of channels of
information flow within the information-processing system and assumed that the
system was limited in capacity (Neumann, 1984). However, the incompleteness of
this conception of information-processing led to the emergence of two distinctions
within this framework; "processing could either be controlled by the subject, or
determined by the structural features of the system; and it could either require
capacity or be free from capacity requirements" (p.257, Neumann, 1984). This
incompleteness also paved the way for two-process theories of information-
processing (LaBerge & Samuels, 1974; Posner & Snyder, 1975; Schneider & Shiffrin, 1977), which combined these two distinctions such that processing could be conscious, controlled and require capacity, or be automatic, free of capacity limitations and unavailable to conscious awareness (Neumann, 1984).

2.5.1 Two-process theories of information processing

Much of the current theorizing on the nature of automatization and human information processing, and the terminology used to explain various experimental phenomena, has its origins in the work of LaBerge & Samuels (1974), Posner & Snyder (1975) and Schneider & Shiffrin (1977; Shiffrin & Schneider, 1977).

LaBerge & Samuels (1974) investigated the process of reading, which when fluent appears to be a unitary process, although they considered that it consisted of a number of component sub-skills which gradually become “automatic” after extended practice and experience. For example, perhaps the most basic sub-skill would be the detection of certain visual features of letters (i.e. line length, vertical or horizontal orientation) in order to allow discrimination between various letters. Under the proposed model, it was considered that initially this process would require attention to allow the features extracted to be organized or linked in such a way as to create a letter code by which an individual letter could be identified. With practice, this letter code would automatically (without attention) be activated upon reading a given letter, rather than requiring the initial feature detection process to be carried out consciously. Reading becomes automatic after extended practice because the component sub-skills of reading become automatic.

Posner & Snyder (1975) investigated the ways in which conscious strategies and automatic activation interact during performance of tasks. They considered cognitive tasks to be accomplished using a combination of automatic activation and conscious strategies, such that a person can consciously direct their attention to an informational input and perform operations on that information. They labeled such activity as a program or strategy, and although such programs can direct attention and hence filter information, they cannot prevent the build up of information due to automatic activation. It was considered that concentration on a particular input has the effect of reducing the probability that other processes will intrude on conscious awareness, and the fact that effort is required to maintain concentration on a given
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input is taken as evidence that the automatic activation effects of other stimuli cannot be completely ignored.

Operations carried out by the conscious processing system are viewed as being dependent upon the limited capacity of that system and as such can be distinguished from automatic activation processes, which are defined in terms of three properties: they occur without intention, without conscious awareness and without causing interference with (or experiencing interference from) other activities (Posner & Snyder, 1975). These three characteristics are usually viewed as being the primary criteria of automaticity (Neumann, 1984), although other “secondary” criteria are also offered by various researchers as being definitive of automaticity (Shiffrin & Dumais, 1981; Hasher & Zacks, 1979; but see Neumann (1984) & Bargh (1992)).

Schneider & Shiffrin (1977) and Shiffrin & Schneider (1977) proposed that human information processing could be described in terms of two dichotomous processing modes; controlled and automatic processing.

Under this model, memory is conceived of as a large collection of complexly interconnected nodes which become increasingly inter-associated through learning. The short-term memory store is described as the set of currently activated nodes whereas the long-term store is referred to as the set of inactive nodes, containing learned sequences of information processing which can be activated by internal or external input of a specific or general nature. Once activated, these sequences are “executed automatically” and make “few demands on the capacity of the short-term store” (Schneider & Shiffrin, 1977, p.2). The learned sequences of nodes contain relatively permanent associative connections, require consistent training to fully develop, and once learned are difficult to suppress, modify or ignore.

On the other hand, a controlled process is seen as a “temporary sequence of nodes activated under control of, and through attention by, the subject” (Schneider & Shiffrin, 1977, p.2). The requirement of active attention means that only one sequence at a time may be engaged, and so control processes are limited by the available capacity of the short-term store (but may be easily altered), and can be applied in novel situations for which no learned sequences exist.

Schneider & Shiffrin (1977) investigated these modes of processing using a visual/memory search task derived from Sternberg’s (1966) memory search task. At the beginning of each trial subjects were presented with a single frame containing a set of consonants or digits. This was called the memory set and the task of the subject...
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was to detect the presence of any of the memory set items in a succession of other
search frames (display sets) presented after the memory set and containing another set
of consonants. Consequently, memory set items were referred to as targets, whilst
non-memory set items occurring within the search frames were referred to as
distractors.

In the consistent-mapping condition, memory set (target) items were chosen
from a different group of stimuli (digits) than the distractors (consonants). In the
varied-mapping condition, memory set items were chosen from the same group of
stimuli (consonants) and items constantly changed roles between trials, being a target
during one trial and a distractor in another trial.

Consistent-mapping stimulus-response relations led to faster and more
efficient performance that was characteristic of automatic processing and which was
unaffected by increases in memory set or display set size. Varied-mapping stimulus-
response relations led to controlled visual search of the display sets that was slowed
by increases in the size of the memory set and the display sets.

Schneider & Shiffrin (1977) concluded that automatic processing develops
through the initial use of control processing which links the same nodes together in a
sequence. Once these sequences are well-learned, information can be processed
without consuming short-term store capacity.

Beginning with this research and continuing with other subsequent work, a
conception of human information processing as being accomplished by two opposite
processes was established. Under this dichotomy, non-automatic processes were
defined as effortful (Hasher & Zacks, 1979), conscious (Posner & Snyder, 1975) or
controlled (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). These processes
are demanding of attentional capacity (Shiffrin & Schneider, 1977) and hence both
decrease the system capacity available for other processing (Shiffrin & Dumais, 1981)
and are limited by the available capacity (Schneider, Dumais & Shiffrin, 1984). They
operate in a sequential fashion and are used in novel or inconsistent situations where
stimulus-response relations vary over time (Schneider, Dumais & Shiffrin, 1984).

Automatic processes, on the other hand, are fast and occur in parallel, are
fairly effortless and are used to perform well-developed, skilled behaviours
(Schneider, Dumais & Shiffrin, 1984). Automatic processes develop as a result of
practice with consistent stimulus-response relations (Shiffrin & Schneider, 1977;
Logan, 1979).
2.5.2 Characteristics of automatic processes

A large proportion of the work on automatization has focused on identifying the properties of automatic processes and determining which properties are evident (or whether some co-occur) in performance of different tasks.

Automatic processing has been described as being fast (Posner & Snyder, 1975; Schneider, Dumais & Shiffrin, 1984), effortless (Schneider & Shiffrin, 1977; Logan, 1979), autonomous (Posner & Snyder, 1975; Shiffrin & Schneider, 1977; Zbrodoff & Logan, 1986), consistent (Logan, 1988; Naveh-Benjamin & Jonides, 1984) or inflexible (Schneider, Dumais & Shiffrin, 1984; Shiffrin & Dumais, 1981) and unavailable to conscious awareness (Shiffrin & Schneider, 1977; Schneider, Dumais & Shiffrin, 1984; Kahneman & Treisman, 1984).

The autonomy of automatic processes, that is, the tendency for a process to be carried out without (or even against) intention can be evidenced by the Stroop effect (Stroop, 1935) and the phenomenon of spreading activation in long-term memory, whereby a word activates its own representation in memory as well as representations of other related words (Warren, 1972). The ballistic nature of automatic processes is also evident from a study by Logan (1983), who asked subjects to occasionally inhibit their responses when making category and rhyme judgments about pairs of words. It was found that memory for words whose responses were inhibited was not significantly different from memory for words with non-inhibited responses, suggesting that simple thoughts ran on to completion even when responses to those stimuli were cut short.

Shiffrin & Schneider (1977) found evidence of autonomy from two different experiments; familiar stimuli (consistently mapped targets from a previous task) placed in display locations that were meant to be ignored by the subject were found to interfere with visual search in other attended areas of the display. This suggests that the targets were attracting attention against the intention of the subjects. Further evidence is provided by the performance difficulties faced by subjects when the roles of targets and distractors were reversed after extended consistent-mapping training (Shiffrin & Schneider, 1977). Performance dropped below the level seen at the beginning of the initial training task and took longer to return to levels comparable with the end of the original training. It would seem that subjects had difficulty ignoring items which had previously been targets, suggesting a need to unlearn
responses to the previous memory set or to overcome a learned inhibition to the previous distractors (Shiffrin & Schneider, 1977).

Such results are also evidence of the inflexibility of automatic processes, since the automatic processes continued to detect old targets even though the goal of the task had changed. Shiffrin & Dumais (1981) suggest that automatic processes act as separate units with fixed beginning and end points, making it difficult to begin an automatic process in the middle of the sequence (i.e. starting to play a passage of music from the middle). Control processes, on the other hand, can be started and ended at any point in the learned sequence of action or thought, and hence are easily modified.

Effort required in performance of a task cannot be quantified directly but has often been indirectly measured in terms of load effects associated with visual-search tasks and interference in dual-task paradigms (Logan, 1985).

In the visual-search paradigm of Schneider & Shiffrin (1977) and Shiffrin & Schneider (1977), for the consistent mapping condition, load effects due to increases in display size or memory-set size decreased significantly with practice. Eventually, after extended practice, performance (measured in terms of reaction time and accuracy) became virtually independent of display size and memory-set size. The absence of such load effects led Shiffrin & Schneider (1977) to propose that “a qualitatively different process, automatic detection, was operating in the consistent-mapping conditions” (p.128) compared to the control processing of the varied-mapping conditions, in which performance was sensitive to manipulations of display and memory-set size.

Absence of load effects is also suggestive of another characteristic of automatic processing related to effort, namely parallel processing, whereby an automatic process should be able to be performed simultaneously with another process and not interfere with that concurrent process (Schneider, Dumais & Shiffrin, 1984; Kahaneman & Treisman, 1984; Shiffrin & Dumais, 1981). A number of studies have shown that after extended practice in a consistent environment, subjects have been able to perform complex tasks simultaneously, with little or no dual-task interference. For example, subjects have been able to read and transcribe dictation with no significant loss of reading speed or comprehension compared to the reading-only condition (Spelke, Hirst & Neisser, 1976; Hirst, Spelke, Reaves, Caharack & Neisser, 1980), type whilst shadowing prose (Shaffer, 1975) and perform ordered
recall of strings of digits whilst performing a multiple-choice reaction-time task (Logan, 1979).

The unavailability of automatic processes to conscious awareness is reflected in the poor memory for performance dominated by automatic processes. It is a phenomenon which is evident in the small slips and lapses that occur in everyday life, such as pouring a second kettle of water into a freshly made pot of tea, or having no recollection of performing a daily routine such as shaving (Reason, 1984; Norman, 1981). The few experimental studies that have investigated memory for automatic processing concur with the common perception of poor memory for automatic processes. A study of reading by Kolers (1975) found that subjects had poorer memory for the exact words of normal text than for spatially transformed text. Kolers (1975) suggested that this was due to the automatic nature of normal reading and this was supported by the finding that memory for the transformed text declined with practice (as reading skill increased).

2.5.3 Conditions that promote the development of automatic processes

Much early work on automatization focused on establishing the conditions necessary for the development of automatic processing.

Repetition is one of the conditions most fundamental in promoting behaviour to become habitual, or for automaticity to develop. Evidence from Stroop and dichotic listening studies shows that stimuli can automatically activate internal representations with which they have been habitually associated, such that the automaticity of a process is a function of the degree of experience one has had with those associations (Posner & Snyder, 1975).

In referring to multiple-task performance, Hirst, Spelke, Reaves, Caharack & Neisser (1980) claimed that humans “can learn to do indefinitely many things indefinitely well” (p.114) and that all that is required is extended practice on the task. However, it would appear that the situation is not quite that simplistic; the quality of practice is very important in determining the extent to which automaticity develops. Simply extending practice on dual-tasks alone is not sufficient to facilitate development of automatic processing (Logan, 1979; 1980; Schneider, Dumais & Shiffrin, 1984). Consistent stimulus-response relations are necessary so that a particular response may become associated with a particular stimulus as practice takes
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place (Schneider & Shiffrin, 1977; Schneider & Fisk, 1982a; 1982b; Logan, 1979; Schneider, Dumais & Shiffrin, 1984).

The importance of consistency in developing stimulus-response relations was made evident by Schneider & Fisk (1982b) who found evidence of graded automaticity in response to variations in the ratio of consistent mapping. The number of times an item appeared as a target was kept constant whilst the number of times it appeared as a distractor was varied. Detection accuracy decreased as the ratio of consistency decreased, with no improvement on initial performance being seen for trials when an item was a target half as often (33% consistency) or one-seventh as often (12.5% consistency) as it was a distractor. Importantly, automaticity can be seen to develop under conditions of less than perfect consistency, but equally it is also evident that inconsistency can slow the rate of development of automatic processing or even prevent it entirely (Shiffrin & Dumais, 1981).

Kramer, Strayer & Buckley (1991) also investigated the role of consistency in the development of automatic processing. Subjects performed a memory/visual search task under consistent and varied mapping combinations of both attending and responding to the stimuli; the response (bi-directional joystick movement to indicate yes or no) to a consistently-mapped or variably-mapped task could be consistently or variably-mapped itself. The results showed that automaticity can develop in the absence of consistent responding and suggest that, since consistent-mapping of the entire task is not necessary, performance may be able to be improved by practicing only the critical components of a task (Kramer, Strayer & Buckley, 1991).

Schneider & Fisk (1980-cited in Shiffrin & Dumais, 1981) investigated how success in detection of consistently mapped targets affected the development of automaticity. They found that detection accuracy increased with the total number of detections made but that when the number of successful detections was held constant (4), an increase in the number of non-detection trials (from 2 to 16) reduced the rate of automatization, suggesting that a major factor in the development of automaticity may be the ratio of detection trials to non-detection trials (Shiffrin & Dumais, 1981).

A further condition that appears necessary for a behaviour to become automatic is that the stimuli themselves must be discriminable from other distracting stimuli. The stimuli need to be unambiguous, such that attention is not required to discern a stimulus from other competing stimuli (distractors) or the stimulus background (Schneider, Dumais & Shiffrin, 1984; Shiffrin & Dumais, 1981). For
example, Hoffman, Simons & Houck (1983) found that severely degraded stimuli did not show the parallel, capacity-free processing characteristically associated with automatic processing, even when the stimuli were presented in a consistent manner.

Other factors affecting development of automatization are the distribution and history of training, the type of task, and the context in which the task is performed (Shiffrin & Dumais, 1981).

### 2.5.4 Resource theories of automatization

Whilst a number of studies focused on the conditions required for the development of automatic processing, others concentrated on proposing a mechanism by which automatization develops.

Resource or capacity theories assume that human information processing involves the utilization of a single resource or a collection of limited-capacity resources (Wickens, 1980; 1984).

Single-capacity theories propose that a single resource, attention, mediates task performance, such that performance improves as more attention is allocated to a task and declines as attention decreases or is directed away from the task, as during dual-task performance when a secondary task attracts attention away from the primary task. The development of automaticity is viewed as a reduction in the level of attention required to perform a task, with automatic processing being capacity- or attention-free, and stems from observations of diminishing attential effects with practice, such as absence of load-effects in search tasks (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977) and reduced dual-task interference (Fisk & Schneider, 1982a; Fisk & Schneider, 1983; Hirst et al., 1980; Logan, 1979; Spelke et al., 1976).

However, there appears to be little evidence that processing is free of capacity restraints (Cheng, 1985; Neumann, 1984), since attentional effects have been found for tasks thought to be performed automatically (Hoffman, Nelson & Houck, 1983; Paap & Ogden, 1981). Furthermore, the undifferentiated resources model has difficulty accounting for four phenomena found in dual-task situations: 1) Difficulty insensitivity, whereby an increase in the difficulty of a primary task fails to adversely affect performance on a secondary task; 2) Perfect time-sharing, in which two tasks are performed as well as either task can be performed alone; 3) Structural alteration of the processing of a task changes concurrent task interference even though the
difficulty of the task remains unaltered; 4) Difficulty/Structure uncoupling - the more
difficult of two tasks causes less interference than the easier task when paired with a
third task. These shortcomings and observations of reduced dual-task interference
with increasing differences between concurrent tasks led to the proposal of the
existence of multiple resources within the human information processing system, each
being able to be shared and allocated flexibly to concurrent tasks (Wickens, 1980;
1984).

Wickens (1980; 1984) argued for a differentiation of such resources along
three dimensions; stages of processing (perceptual & central processing versus
response processing), the coding of that processing (verbal versus spatial) and the
input (visual versus auditory) and response (manual versus vocal) modalities. The
implication of such a model is the suggestion of the modular organization of the brain
(Kahneman & Treisman, 1984), such that interference will occur within the
subsystems if two tasks demand the same resources - the more separate the resources,
the more efficient time-sharing will be (Wickens, 1984). Therefore, interference is an
emergent property that is specific to a combination of tasks and not dependent upon
the nature of a single task (Logan, 1985; Neumann, 1984).

From the multiple resources view of learning and attention, the development
of automaticity is conceived of as the gradual reduction in the utilization of resources
as learning progresses (Logan, 1979; Schneider & Fisk, 1982; LaBerge, 1973). In
dual-task situations, perfect-time sharing can occur as long as one of the tasks is
automatic and is possible because the minimal resources required by the automatic
process leave enough capacity for performance of the other (control processing) task.

For example, Fisk & Schneider (1983) found that subjects performing a
simultaneous automatic visual category search and digit-span task showed less than a
two percent deficit in performance for each task. Also, decrements in consistent-
mapping semantic search caused by simultaneous performance of varied-mapping
digit search have been shown to decrease substantially with practice, indicating a
reduction in resource requirements for an automatic search task. Schneider & Fisk
(1982) also showed that automatic processing (consistent-mapping search) can be
carried out concurrently with controlled processing (varied-mapping search),
suggesting that automatic processes are insensitive to resource reductions caused by
control processes.
However, lack of dual-task interference does not necessarily mean that one or both tasks are automatic; a shift in resources during learning may lead to different resources being used for automatic processing than for initial, effortful processing, such that there is little overlap (and hence competition) between the tasks for the resources they both require (Neumann, 1984).

The re-stating of the single resource answer that automaticity reflects a reduction in the amount of resources required to perform a task implies that a completely automatic process will require no resources at all, “which is antithetical to the basic assumption of multiple resource theory; namely, that every task or process requires some resources” (p.376, Logan, 1985). Another possibility, that there exists an executive resource which directs the other resources during task performance, again raises the problem of identifying that resource. Also, it may be that there is no single executive - different resources may assume an executive role for different tasks (Logan, 1985).

Multiple resource theory provides an intuitive description of the reason for automatization but no specific mechanism is proposed to explain how resources diminish with practice (Logan, 1988b; 1992). The concept also raises some difficult theoretical problems, since it is impossible to; a) identify which resources are used in performing a given task or; b) to quantify the capacity of each resource (Logan, 1988b).

Even the very concept of resources has been questioned as to its validity and usefulness in describing information processing. Navon (1984) points out that the concept of resources was introduced as a “hypothetical common currency” in order to explain the trade-off between cognitive processes and not as a real-life, mental entity in itself. It is a convention that has tended to be reinforced in the absence of well-specified alternatives. Resource theory proposes that some processes do not require resources and makes no attempt to identify processes (or the properties of those processes) that do require resources, and also has “built-in escapes...such as, data limits, operation below full capacity, disparate resource composition, and so forth” (p.231) that can be used to account for anomalous experimental results. As such, Navon (1984) contends that resource theory “enjoys the status of an existential claim” (p.231); it is unfalsifiable and only evidence in support of the theory is considered relevant.
2.5.5 Restructuring

Due to the difficulties of explaining automatization in resource terms, attempts have been made to account for learning and skill acquisition without invoking the concept of automatization-as-a-reduction-in-resources.

Hirst, Spelke, Reaves, Caharack & Neisser (1980) suggested that extended practice in a dual-task situation is sufficient to develop automatic processing and that this automaticity does not take the form of a reduction in resources. They proposed that the ability of subjects to simultaneously read and take dictation could be explained in terms of the learning of new stimulus and action patterns, rather than the alternation of attention or automatization (development of capacity-free processing) of one of the tasks (but see Shiffrin & Dumais (1981) for an alternative explanation of these results). Hirst et al. (1980) suggest that “component perceptual or motor processes are changed by becoming embedded in larger schemas and may lose their independent existence entirely” (p.115). This amounts to a conception of a restructuring of processes and is also proposed by Cheng (1985) to explain learning in consistent-mapping visual search (ie. Shiffrin & Schneider, 1977).

Cheng (1985) suggested that there is little evidence for capacity-free processes beyond the stage of physical-feature processing (see also Neumann, 1984), and therefore automatization-as-capacity-free-processing cannot account for results indicating reduced or negligible dual-task interference, or no effect of increases in memory-set or search display size. Rather, restructuring, which takes the form of the use of a categorization strategy to classify targets and distractors on the basis of perceptual features, produces flat set-size functions by reducing the need to fully process or compare display-set items. In this case, targets and distractors are each given a category tag that identifies the category to which they belong. Efficient processing would only require comparison of the category tags (and not the entire stimulus), and so a reversal of stimulus-response mapping should not affect performance, since the categories will not have changed - only the response to each category has changed.

However, Shiffrin & Schneider (1977) specifically investigated this hypothesis (Expt. 3) by exchanging the roles of targets and distractors (targets became distractors and vice-versa). These and other results showing poor transfer of skill to a reversal of stimulus mapping led to the conclusion that categorization and visual
Automaticity discrimination alone cannot provide a viable explanation for the observed improvement in performance (Schneider & Shiffrin, 1985).

The automatization-as-restructuring and automatization-as-a-reduction-in-resources approaches both assume that automaticity develops as a result of improvement in the processes underlying performance. Whereas resource theories view automatization as being the result of making underlying processes more efficient - by reducing the number of resources required to perform the task or reducing the number of steps involved in the task (LaBerge & Samuels, 1974; Anderson, 1982) - restructuring proposes that the task is performed differently after practice, not just more automatically. For example, Cheng (1985) suggests that in the case of learning to perform multiplication, restructuring takes the form of a change from iterative addition to the actual multiplication process, which implies a significant change in the processes underlying performance.

There does appear to be some evidence that learning involves changes in the processes underlying performance. Schneider & Fisk (1984) found evidence of transfer of a category judgment task; subjects were trained to detect consistently-mapped words that were members of the category “colours” and were later presented with new exemplars of the category and showed positive transfer, even under a high workload (dual-task) condition. They concluded that consistent attention to a class of stimuli within a salient context will bias processing of that class of stimuli. Re-experiencing that context activates an attentional filter that will selectively pass information that is semantically similar to the stimuli previously encountered.

This finding is an example of cognitive set learning, which refers to the “preparation in advance for the probabilities or contingencies characterizing a given situation” (Fitts, 1964, p.270) and relates to the issue of specific versus generalized learning effects. People develop cognitive sets to prepare themselves to respond appropriately within a certain context or situation, and many of these sets will overlap in terms of the stimulus and response elements that belong to those sets (Fitts, 1964). Cognitive sets will change as the context of a task changes; for example, if the instructions of a task are changed from giving the meaning of words to giving the opposite meaning of words (Fitts, 1964).

It appears that the relative importance of cognitive sets and associational processes is dependent on task coherence, a term relating to the fixedness of the stimulus-response relations of a particular task. Highly coherent tasks have rigid
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stimulus-response relations, whilst low coherence tasks will have a large number of response patterns associated with a particular stimulus (Fitts, 1964). In such situations, the probability of occurrence of stimuli will affect the rate of learning and cognitive sets become more important because the probability of those occurrences needs to be learned, rather than each stimulus-response relation (Fitts, 1964). Highly consistent stimulus-response relations are not available, so subjects need to develop strategies for responding correctly under situations that might be slightly different from each other but require a similar response.

Cognitive set learning is evident in the case of extensive learning of stimulus-response relations, suggesting that such "cognitive factors are implicated in all types of highly practiced skills" (p.273, Fitts, 1964). Cognitive set learning governs preparedness to respond in a given manner, and is not necessarily directly involved in the learning of stimulus-response relations. Cognitive set learning can be thought of as the learning of a mode of thought or action, rather than the actual learning of those actions\thoughts (Fitts, 1964).

Despite difficulties in identifying the exact nature of changes in underlying processes supporting performance, it is likely that restructuring may be involved, either as a separate mechanism to automaticity or as a mechanism by which automaticity comes about (Brown & Carr, 1989) and it is difficult to rule out as a contributing factor in skill acquisition (Logan, 1988a).

2.5.6 Difficulties with the two-process view of automaticity

“Property list approaches” (Logan & Klapp, 1991) have attempted to investigate automaticity by defining the characteristics of automatic processing. However, difficulties in agreeing on which criteria are characteristic of automatic processes has led to general disenchantment with such approaches (see Logan & Klapp, 1991). For instance, Posner & Snyder (1975) suggested three criteria by which to define an automatic process whilst Hasher & Zacks (1979) listed five properties, and Shiffrin & Dumais (1981) proposed a list of thirteen possible identifying characteristics.

A further problem with this view is that the defined properties do not appear to be valid. Most automatic processes are not completely free from experiencing or producing interference, nor are they independent of intention or direction of attention.
Automaticity (Neumann, 1984). For example, the automatic detection of a target interferes with detection of another simultaneous target (Shiffrin & Schneider, 1977, Expt.4) and interference on the Stroop task has been shown to decrease if target and distractors are perceptually (Francolini & Egeth, 1980) or spatially (Egeth, 1977) separated.

Another problem with the two-process view of automaticity is that it is a unitary one in which a cognitive process can be defined “as either controlled or automatic - possessing all the features of one and none of the other” (p.182, Bargh, 1992). However, this definition of automaticity (in which all the properties must co-occur for a process to be defined as automatic) is flawed since such properties “seem to co-occur in just about any combination” (Bargh, 1992, p.183).

Also, there appear to be dissociations between the properties of automatic processing and controlled processing. For example, effortful processes have been shown to be autonomous (Regan, 1981) and autonomous processes have been shown to be effortful (Paap & Ogden, 1981). Similarly, Hoffman, Nelson & Houck (1983) found that a visual search task that was thought to be automatic showed evidence of dual-task interference - a shift of attention to the spatial location of the stimulus was required for correct detection of that stimulus, and prevention of this shift impaired detection accuracy. Zbrodoff & Logan (1986) found that arithmetic processes (addition and multiplication) are autonomous, in that they can begin without intention, but are not completely autonomous, since they can be inhibited after having begun and so do not run onto completion without intention.

A further dissociation is the fact that skilled processes appear to be highly controlled. Skilled typists (Logan, 1982) and adult speakers (Levelt, 1983) were shown to be able to inhibit performance within one or two keystrokes or syllables (respectively) of receiving a signal to stop or detecting an error, suggesting that automaticity and control cannot be opposites.

These results would seem to suggest that the concept of automaticity is internally inconsistent, but Logan (1985) argues that such results reflect only the partial automaticity of such processes. That is, a process that is not fully automatic will show characteristics of control processes, such as interference and effort (and control processes may show characteristics of automatic processes).

Logan (1985) argues that the dichotomous model may be an inappropriate way to view the concept of automaticity, and that given the close relation between automaticity and skill, it may be more productive to view automaticity as a continuous
dimension (like skill), rather than a dichotomy. That is, a process can be less or more automatic, just as a person can be less skilled or more skilled than another person (Logan, 1985).

Support for a continuous model also comes from the results of a neural network simulation of the Stroop effect. Cohen, Dunbar & McClelland (1990) modeled the Stroop effect as resulting from the competition between two parallel pathways or processes (word-reading and colour-naming) that differ in degree of automaticity depending on the amount of practice experienced for each process. This contrasts with the usual model of the Stroop effect, which explains the phenomenon as a conflict between an automatic process (reading) and a controlled process (colour-naming). Given evidence suggesting that few, if any, tasks are immune from the effects of attention (Neumann, 1984; Cheng, 1985), Cohen, Dunbar & McClelland (1990) also suggest a role for attention, which is assumed to modulate processing by altering the responsiveness of a pathway (word-reading or colour-naming) used to carry out the Stroop task.

Despite being a continuous model, the concept of controlled processing is not rejected, and is suggested to be a valid way of addressing the issue of unpracticed task performance (Cohen, Dunbar & McClelland, 1990). Controlled processing is assumed to be used to establish indirect pathways in the initial stages of performance, after which practice starts to build direct pathways or connections between stimuli and responses (see also Shiffrin & Schneider, 1977). These direct connections remove the need for indirect processes, such as verbal mediation or mnemonics (Cohen, Dunbar & McClelland, 1990). Such a model is classed as a strength model, as it explains learning as developing through the strengthening of connections between units in a particular pathway.

2.5.7 Summary

The single-capacity view of automaticity has been superseded by the multiple-resources view on the basis of evidence showing that interference between simultaneous tasks is dependent upon the modality of “input, output and central processing” (Logan, 1988b, p.585; see Wickens, 1980; 1984). However, the multiple resource view has its own conceptual problems, such as identifying and quantifying
which resources are used to perform particular tasks and providing a learning mechanism to account for the development of automaticity (Logan, 1988b).

Also, the view that automatic and controlled processes are opposites (Shiffrin & Schneider, 1977; Posner & Snyder, 1975) is not supported since automatic processes have been shown to be highly controlled (Levelt, 1983; Logan, 1982), and it has even been suggested that characterising automaticity as a dichotomy may not be scientifically useful (Newell, 1973).

Clearly, the two-process view, which has dominated the literature on automaticity, has a number of difficulties that remain to be resolved (Logan, 1988b).

2.6 Memory theories of automatization

An alternative approach to the development of automaticity is to view automatization as a memory phenomenon. From this perspective, automatization is seen as an accumulation of information in memory and automatic performance is considered to depend on “single-step, direct-access retrieval of solutions from memory” (Logan, 1988b, p.586). Novices are assumed to perform tasks using a multiple-step algorithm and hence, automatization involves a transition from algorithmic to memory-based performance (Logan, 1988a).

A number of mechanisms by which automaticity may develop have been proposed. The first of these is strengthening, whereby practice strengthens connections in memory between specific stimuli and specific responses (i.e. Anderson, 1982; MacKay, 1982; Schneider, 1985). The second is based on the idea of chunking, in which responses to stimulus patterns are acquired by the subject and stored as chunks of information. The chunks can have differing levels of complexity, encompassing anything from a single element of the stimulus up to the entire stimulus. Smaller patterns or chunks (those encompassing the fewest elements) are encountered and practiced more often than larger chunks because they are applicable to a greater range of situations, such that the rate of learning is greatest initially and declines as the chunks become organized into larger and more complex patterns, and are applicable to fewer, more specialized situations (Newell & Rosenbloom, 1981).

The third mechanism is related to a theory of memory (Hintzmann, 1976) and involves instance representation of stimuli in memory; that is, each encounter with a stimulus forms a separate trace in memory, resulting in multiple
representations of individual stimuli. Also, both the processes of encoding and retrieval of each trace (instance) are assumed to be obligatory consequences of attention; that is, attention to a stimulus is sufficient for it to be encoded or retrieved from memory along with whatever else was associated with that stimulus in the past (Logan, 1988a).

Evidence for obligatory retrieval comes from studies showing that presentation of a word also activates associates of that word (Warren, 1972; 1974). However, this does not mean “that all items will be encoded equally well” (Logan, 1988a). For example, Craik & Tulving (1975) showed that memory for items is dependent upon the level of processing that the item undergoes - memory for semantically processed words is better than for words processed on a physical basis. Differential memory for stimuli is also evident from a study showing facilitation of recognition recall of recently associated words (Ratcliff & McKoon, 1981).

The existence of separate memory traces is suggested by evidence of the storage in memory of information identifying separate traces of identical stimuli. Hintzmann & Block (1971) showed that, for a word that is repeated in a list, the positions of those repetitions can be accurately judged, suggesting that a temporal cue may be used to ‘tag’ each trace (see Hintzmann, 1976).

The instance theory of automatization models the transition from algorithmic to memory-based performance as a race between the algorithm and memory-retrieval (Logan, 1988a). The algorithm races against the fastest instance retrieved and serves to screen out slow and ineffective retrievals by finishing first and providing the solution to the problem, but as practice continues, memory-retrieval comes to dominate performance. The statistical model of the race assumes that the distribution of algorithm finishing times remains relatively constant whilst the distribution of retrieval times is governed by the power law of learning, which describes an overall speed up in processing and a simultaneous decrease in the learning rate. The speed-up in processing is attributed to the increasing probability of observing extreme values (low response times) as the number of trials increases, whilst the decrease in the learning rate is seen as a result of the decreasing probability of sampling a value that is more extreme than the previous one as the number of trials increases. Therefore, memory eventually guides performance because retrieval times become faster than the finishing times of the algorithm (Logan, 1988a). As well as predicting a power function decrease in mean retrieval times, instance theory also predicts a decrease in
the variability of the retrieval times which also follows the power law and has the same exponent as the power function for the mean.

Instance theory accounts for the observed properties of automatic processes by suggesting they are also the properties of memory retrieval (Logan, 1988a). As the number of experiences or encounters with a stimulus increase, so does the number of traces available in memory at the time of retrieval and the faster and more reliable retrieval becomes. Automatic processing is effortless because memory retrieval is effortless and only wins the race with the algorithm when associative strength is high and retrieval is reliable enough for solutions to come to mind easily (Logan & Klapp, 1991). At all times, the subject can use the algorithm or memory retrieval to solve the problem, but presumably would not use retrieval until it was at least as fast, reliable and effortless as the algorithm (Logan, 1988a). Single-step retrieval provides no intervening stages on which to introspect, and so automatic performance is unavailable to conscious awareness (Logan, 1988b).

2.6.1 Evidence for item-based learning

Whereas the resource view argues that automatization involves process-based learning, instance theory proposes that “subjects learn specific responses to specific stimuli” (Logan, 1988b, p.588), and that automaticity involves item-based learning. A number of results seem to support this proposition.

Benefits from repetitive encounters with stimuli were found to be specific to individual stimuli, indicating that subjects remembered previous exposures to those stimuli, and hence provide evidence of separate representations in memory (Logan, 1988a). A lexical decision task (deciding whether a letter string was an English word) showed substantial decreases in response time with practice for items that were repeated (sixteen exposures), but not new items (one exposure), suggesting that performance in that particular domain may involve learning specific responses to stimuli (learning was item-based rather than process-based). Process-based learning would have resulted in a further decrease in response time after the introduction of the new items; the process of lexical decision itself would have speeded up, allowing quick responses to stimuli (new items) that had never been encountered before (Logan, 1988a, Expts. 1-3).
Further evidence for item-based learning comes from results of frequency judgments of individual stimuli (Logan, 1988a). A consistently-mapped and variably-mapped task involved lexical and pronunciation decisions about words, pronounceable non-words and unpronounceable non-words, after which subjects were transferred to the frequency-judgment task. According to instance theory, frequency judgments would be made using separate representations of the stimuli in memory and should show no difference between the mapping conditions, whereas according to strength theories, the varied-mapping would prevent strengthening of stimulus-response connections, resulting in poor estimation of frequency of presentation of the stimuli. Frequency judgments for the mapping conditions were found to be very similar, suggesting that subjects maintained separate stimulus representations even though they were not used to support frequency judgment (Logan, 1988a, Expt.5).

### 2.6.2 Evidence for memory retrieval in automatic performance

Since memory theories assume that automatic processing involves single-step, direct retrieval from memory, performance on a memory-search task should not require a representation of the memory-set to be present in working memory. Strayer & Kramer (1990) investigated this possibility using a consistently-mapped and variably-mapped memory-search task with an additional manipulation. On half of the trials, an interference task (monitoring and responding to a sequence of 15 digits) was performed in between the presentation of the memory set and presentation of a cue (an asterisk) which preceded the probe stimulus. This task was very demanding and prevented rehearsal of the memory-set, thereby requiring retrieval of the memory-set from long-term memory. This was labeled the secondary memory condition; the primary memory condition did not involve the interference task.

Since varied-mapping prevents consistent stimulus-response relations from developing in memory, performance under such conditions is assumed to be mediated by an algorithm. Algorithmic calculations are performed in working memory, and as such, would be affected by the interference task (which required sections of the digit sequence to be held in working memory). Consistent-mapping promotes the development of consistent stimulus-response relations, and asymptotic performance will be governed by direct access memory-retrieval of solutions and should not be
affected by the status of the memory-set in working memory, thereby allowing perfect time-sharing of the interference task with the memory search task.

For the consistent-mapping condition, Strayer & Kramer (1990) found that the difference in reaction time between the primary and secondary memory conditions decreased with practice, indicating that the interference task was having less effect on performance of the memory-search task as practice continued. By the 8th and 9th session, the reaction time difference between the primary and secondary memory conditions was virtually negligible, and a decrease in the effects of memory load was also temporally coupled with this decrease in reaction times. The varied-mapping condition showed no significant changes in these effects.

The differences between the consistently-mapped and variably-mapped conditions suggest that learning was item-based, which is consistent with memory theory accounts of automaticity (e.g., Logan, 1988a). Theoretically, at the learning asymptote, the probability of retrieval finishing before the algorithm will be equivalent in both the primary and secondary memory conditions and the reaction times for each condition will be virtually identical. At this point, performance will not require representation of the memory-set in working memory, and the memory search and interference tasks will be able to be perfectly time-shared (Strayer & Kramer, 1990).

2.6.3 Implications of automaticity as memory retrieval

2.6.3.1 Need for memory traces

Memory theories stress the importance of having traces in memory to support automatic performance, and it appears that how those memory traces become laid down in memory is not particularly important, as long as they are available.

Logan & Klapp (1991) compared the effectiveness of learning-by-doing (performance of an alphabet arithmetic task) and learning-by-remembering (memorization of alphabet arithmetic facts). They found that there was no difference between the two conditions; in other words, the two learning methods appeared to lead to the same memory representation. The only factors affecting the development of automaticity were the number of alphabet arithmetic facts to be learned and the number of trials per item experienced; as the number of facts increased, the learning
rate decreased, and as the number of trials per item increased the learning rate increased (Logan & Klapp, 1991).

This particular study also relates to the debate about implicit and explicit memory (Logan, 1988b) and whether they are two different memory systems (Tulving, 1983 - cited in Logan, 1988b) or whether implicit and explicit memory tasks tap the same memory system in different ways (Jacoby & Brooks, 1984). The results of the study by Logan & Klapp (1991) showing that there is essentially no difference in performance between learning-by-memorization (presumably involving explicit memory) and learning-by-doing (involving implicit memory) suggests that “the distinction may be blurred when applied to automaticity” (Logan, 1988b, p.595).

The view of automatization as the building up of information in memory has a number of implications for current ideas of learning and skill acquisition. Firstly, the poor performance of novices is explained as being due to lack of knowledge rather than a lack of available resources. Practice allows responses to specific stimuli to be memorized such that a person learns solutions and how to apply and generalize them, eventually learning enough to retrieve most or all of the problems in a domain. A good illustration of this is the addition of single-digit numbers by adults; their extremely short response times suggest that they memorize the answers to all single-digit addition problems (Groen & Parkman, 1972), and the results of a related task (alphabet arithmetic) support this (Logan, 1988a; Logan & Klapp, 1991).

2.6.3.2 Over-learning

Memory theories also predict that learning can continue past a criterion point of automaticity because memory retrieval can become more efficient than is needed to simply replace the algorithm. Klapp, Boches, Trabert & Logan (1991) investigated whether practice beyond automatization has any effects on performance.

Subjects performed sequential or repetitive month-saying concurrently with the alphabet arithmetic task. Sequential month-saying was found to interfere with alphabet arithmetic at both the level of novice performance and once alphabet arithmetic had been automatized, but for apparently different reasons. Novice performance of alphabet arithmetic involves counting through the alphabet using an inner speech process and is interfered with by sequential month-saying, which also requires overt speech simultaneously. However, once alphabet arithmetic has been
automatized, sequential month-saying still interferes because both tasks now require retrieval from memory (alphabet arithmetic facts and month sequence) (Klapp, Boches, Trabert & Logan, 1991).

Repetitive month-saying was found to interfere with novice alphabet arithmetic performance because of a conflict between inner and overt speech processes. It only slightly interfered with automatic alphabet arithmetic performance because repetitive month-saying does not require retrieval from memory.

However, once the alphabet arithmetic task had been learned beyond the criteria for automaticity (overlearned), there was a decrease in interference from sequential month-saying and a reduction in error rates and response time for alphabet arithmetic, suggesting that continued practice after the development of automaticity does affect performance (Klapp, Boches, Trabert & Logan, 1991).

It is apparent then that each encounter with a stimulus will have an effect on memory, even though this effect will diminish with practice as the number of trials increases - “adding one trace to zero makes more of a difference than adding one trace to 10 or 1000” (Logan, 1988a, p.514). This suggests that there may be no limit to automatization (Klapp, Boches, Trabert, & Logan, 1991), a position that concurs with observations of skill acquisition after extended practice (ie. Crossman, 1959).

Another implication of automatization-as-memory theories concerns the effects of context. According to instance theory (Logan, 1988a), as learning progresses, the common features of stimuli become stronger and more easily retrievable than the unique features of those stimuli, which get buried in noise (the common features of all stimuli and unique features of other stimuli). This may have implications for skill acquisition. Initially, when unique features are easier to retrieve, context may be quite important in order to enable consistent stimulus-response mapping and establish reliable sequences of thought and action. After extended practice, when sequences are well-learned, context may become relatively unimportant because the differences between stimuli due to such unique features will be harder to retrieve (Logan, 1988b).

**2.6.4 Evidence against Instance Theory**

Evidence of learning without repetition of specific stimulus-response relationships would contradict the instance theory account of the development of
Automaticity. Instance theory states that automatization develops from the build up of multiple traces in memory, which arises due to the repetition of identical item-response pairings. An algorithm governs performance of the task initially, when no traces are available for retrieval from memory, but it is assumed that no improvement in the algorithm occurs with learning.

Speelman & Kirsner (1997) found that an improvement in performance following the power law was evident for a task involving the solving of syllogisms, each of which was unique and none of which were repeated. Subjects were presented with two premises of the form “All of the artists are beekeepers. All of the beekeepers are chemists.” This was followed by a conclusion such as “All of the artists are chemists”. This particular problem was of the form ABBC, but a second type of syllogism of the form BCAB was also used. Subjects were trained on the syllogisms under four different conditions; random, highlighted, blocked and alternating presentation of the two types of syllogism. This was done to promote the development of different perceptual strategies for solving the syllogisms; for example, presenting the syllogisms in blocks of the same type eliminated the need for subjects to identify the type of syllogism. This finding of the development of automatization without consistent stimulus-response relationships contradicts instance theory, which would predict that no improvement could occur because no stimulus-response (premise-conclusion) relationships were repeated. However, Anderson’s (1982) ACT theory accounts for the results by assuming that improvements in productions (algorithms underlying performance) occur with learning (Speelman & Kirsner, 1997).

Also, full or partial transfer was observed in each of the four training conditions for a transfer task that tested subject's abilities to solve the syllogisms under random presentation conditions. Instance theory predicts highly specific transfer, whilst ACT predicts that transfer will depend on the overlap of productions in the two tasks. If the same productions are used in the transfer task, performance will be similar to that observed at the end of training of the original task, but if new productions need to be developed, performance will be slower and less accurate (Speelman & Kirsner, 1997, p.92).

The apparent conflict between the results and instance theory can be reconciled by considering that Speelman & Kirsner’s (1997) results reflect the flexible and adaptive nature of skill acquisition. Learning in highly constrained situations, where specific stimulus-response relations occur and there are few task
Automaticity variations (e.g., arithmetic), appears to result in the development of very specific skills that can only be applied in limited situations. On the other hand, learning in situations in which there is great variation in the task and “the development of general strategies is encouraged” (Speelman & Kirsner, 1997, p.100) appears to result in the development of abstract and highly transferable skills (Speelman & Kirsner, 1997).

Thus, although there are situations for which instance theory is unable to account for certain results (i.e., Speelman & Kirsner, 1997), it does provide a satisfactory explanation of the development of automaticity for tasks involving learning of specific stimulus-response relations, such as arithmetic processing (e.g., Logan, 1988a).

Therefore, following Logan (1988a), this thesis will focus on this special mechanism of automaticity (the development of specific stimulus-response relations), rather than attempting to also incorporate the influences of other general factors that contribute to learning and skill acquisition, or improvements in algorithms underlying performance which may also contribute to the development of automaticity.

2.7 Automaticity and Arithmetic

2.7.1 Automaticity of single-digit addition

Single-digit addition in children appears to involve the use of an algorithm which successively increments a counter by one for each unit of each addend (number element in the equation). With practice, children simplify the process and begin their count with the larger addend, incrementing by one for each unit of the smaller addend (Groen & Parkman, 1972). A problem-size effect was evident in the reaction time data for this study, with a 400-500ms increase in response time for each increment in the size of the minimum addend. However, ties (problems in which both addends are the same, i.e. 4 + 4) showed unusually low response times, and it was suggested that the answers to such problems may be stored in a fast access memory, and remembered rather than calculated (Groen & Parkman, 1972).

By the time adulthood is reached, addition is a highly over-learned skill, and like ties in children’s arithmetic, shows very quick reaction times (Groen & Parkman, 1972). It appears then that adults remember all the answers to single-digit addition problems, so that the addition process is based on memory retrieval of answers rather
than counting (Groen & Parkman, 1972). Adult addition also shows a number of the properties of automaticity in being fast, effortless and obligatory (Zbrodoff & Logan, 1986).

### 2.7.2 The problem-size effect in arithmetic

The existence of the problem-size effect in arithmetic is taken as evidence of the use of an attention-demanding, conscious, controlled process, such as counting (Ashcraft et al., 1992; Groen & Parkman, 1972), whereas lack of a problem-size effect is suggested to be indicative of automatic processing, such as obligatory memory retrieval (LeFevre et al., 1987; Logan, 1988a).

However, defining arithmetic performance as an automatic or conscious process in this manner is not as clear cut as it would seem. The problem-size effect is a reliable effect for addition (Groen & Parkman, 1972; Ashcraft & Battaglia, 1978), multiplication (Stazyk, Ashcraft & Hamann, 1982), division (Campbell, 1985 - cited in Ashcraft, Donley, Halas & Vakali, 1992) and subtraction (Siegler, 1987) in children, but is also observed in adult arithmetic, a process that involves retrieval processes and is considered to be automatic (Ashcraft et al., 1992, p.303).

The fact that a problem size effect still persists in adults suggests that it is a problem of retrieval and that “there must be factors that are correlated with problem-size that contribute to retrieval difficulty” (p.333, Campbell & Oliphant, 1992). For adult arithmetic therefore, explanations of the problem-size effect revolve around the properties of the memory representation of those facts, whereby retrieval time is dependent upon the associative strength between operands and the answer to the problem (Ashcraft et al., 1992).

### 2.7.3 Memory representation of arithmetic facts

Groen & Parkman (1972) noted that the slope relating digit addend and reaction time for adults was 1/20th of the slope for children. They suggested that this may be explained by assuming that subjects predominantly used direct access memory retrieval of the answer but required use of a counting strategy on 1 in 20 trials in which retrieval may have failed. However, research into the efficacy of direct access memory retrieval “has not been fruitful” (p.201, Widaman & Little, 1992) and instead network retrieval models have proliferated.
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Network retrieval models assume “search through a stored network of answers for the correct answer” (p.201, Widaman & Little, 1992). This is conceived of as activation which is assumed to take a measurable amount of time (Anderson, 1985). This assumption suggests that the characteristics of the activation process can be used to predict reaction time and are “related to the practical form of the network of connections between stored facts” (p.202).

Two types of models of network retrieval are postulated. Tabular memory network retrieval models propose that a 2-dimensional table of addends represents arithmetic knowledge in memory, and that production of an answer comes about by activation of the intersection on the table of nodes corresponding to the two addends of the addition problem. Activation is assumed to begin at 0,0, with reaction time increasing with addend size as the activation spreads through the table to the larger numbers. In this way, tabular models assume that there is an ordered relation of numbers in internal representations, in which activation characteristics are a “function of the area or distance traversed through the network” (Widaman & Little, 1992, p.202).

Evidence supporting tabular models comes from findings that measures of activation characteristics can account for reaction times in adult arithmetic. For example, Ashcraft & Battaglia (1978) found that response times to addition problems are more strongly related to the square of the true sum (SUM^2) of the problem, rather than the problem-size. Still others have found that the product of the two addends is a more accurate predictor of response times than the square of the sum (Widaman, Geary, Cormier & Little, 1989; Miller, Perlmutter & Keating, 1984). PRODUCT is currently the most accurate predictor of response times in tabular retrieval models (Widaman & Little, 1992).

In non-tabular models, activation characteristics are a function of the strength of association between problems and correct answers, and also a function of competing associations from related integers and incorrect answers. A structural measure corresponding to product in tabular models, but instead measuring strength of association between correct and incorrect answers and problems, also capably accounts for arithmetic reaction times, and therefore provides strong evidence supporting non-tabular models (Widaman & Little, 1992).

The success of network retrieval models in accounting for the behavioural data of adult arithmetic means that problem-size is now viewed only as a correlate of
problem difficulty or problem strength (Ashcraft, Donley, Halas & Vakali, 1992, p.304).

There is an abundance of further evidence supporting associative network models of arithmetic (Ashcraft, 1987; Campbell, 1987).

The inter-relation of information in memory is suggested by findings that identical regression models can account for addition and multiplication reaction times (Widaman & Little, 1992), and is also suggested by confusion effects, whereby reaction times are slowed when the answer to an equation is correct under a different operation (i.e., $5+4=20$). This effect has been observed in both verification (Miller, Perlmutter & Keating, 1984; Zbrodoff & Logan, 1986) and production tasks (Campbell, 1987). There may also be a similarity between addition and subtraction networks as suggested by findings that response times to false problems that were true for the subtraction operation (i.e. $1+7=6$) were slower than problems that weren’t true for the subtraction operation (Ashcraft & Battaglia, 1978).

Further supporting evidence that arithmetic information is inter-related in memory comes from verification (Stazyk et al., 1982) and production (Campbell, 1987) tasks showing costs associated with the presentation of a prime prior to the presentation of the actual problem. Whilst correct primes have been shown to facilitate speed of performance, false primes slow response times. The slowing effect holds for false primes that are unrelated to the correct answer, but is exaggerated if that prime is related to the actual correct answer for the problem (Campbell, 1987). Related primes are those that are a common error response to a particular problem (Campbell, 1987), and tend to be answers from the same times table in multiplication tasks; for example, if 24 is produced as the answer to $3\times8$, 24 may be an error to a subsequent problem, $4\times8$. Although it might seem plausible that related primes may facilitate retrieval by indirectly activating the correct answer in memory “it seems instead that any prime other than the correct answer yields a disruptive effect. This disruption is, of course, evidence that the prime is indeed activating information in memory, and exerting an influence on the retrieval process” (Ashcraft et al., 1992, p.324).
2.7.4 Factors responsible for the problem-size effect in automatic arithmetic

Zbrodoff (1995) investigated why there was a problem-size effect in adults, a stage at which arithmetic performance should be well-practiced, automatic and effectively with little further improvement to be made.

Zbrodoff (1995) presented arithmetic problems which were dissimilar from each other in order to control for interference effects that affect similar or related problems. After extensive practice, although problems were presented with differing frequencies, there were no differences in response times between the problems. Therefore, differences in strength (based on frequency) were not sufficient to explain the problem size effect (as occurred in Expt. 3) at high levels of practice.

However, for similar problems (Expt.3), although the problem-size effect diminished with practice (suggesting an influence due to strength/frequency), it was evident even at high levels of practice. It was presumed that similar problems would show more interference and the results support this, suggesting that, at high levels of practice, interference may contribute to the problem-size effect due to the similarity of the equations. Experiment 4 used large and small problems shown with equal frequency so that similarity-based interference should be responsible for any problem-size effect. But the problem-size effect was reduced to zero by the end of training, suggesting that similarity-based interference cannot by itself explain the problem-size effect. The results of these experiments suggest that a combination of strength and interference may explain the problem-size effect at high levels of practice. This contrasts with findings suggesting that at low levels of practice, response time is dependent on frequency of encounter (Expt.1, Zbrodoff, 1995).

Hence, different factors appear to be at work at different stages of skill development. Frequency of encounter appears to be the prime factor in performance at low levels of practice, whilst at high levels of practice, interference also becomes a contributing factor (Zbrodoff, 1995). This finding concurs with the way in which expert arithmetic is assumed to be performed (retrieval) and how arithmetic knowledge is thought to be stored in memory (in an associative network) (see Campbell & Oliphant, 1992).

2.7.5 Interference

Interference is viewed as being due to competition between problems with a shared addend, but other types of interference may occur (Zbrodoff, 1995). For
example, it has been shown that subjects make more error responses for large problems (Siegler, 1986; 1988) and that these error responses themselves may serve to interfere with correct problem-answer associations. This is presumably because they strengthen incorrect problem-answer associations (Siegler, 1988).

A number of reasons for an increase in errors on large problems are suggested; large problems may suffer proactive interference as a result of being learnt later, and having larger numbers of competing associations to be differentiated from (Campbell & Graham, 1985). Another reason for increased errors on large problems may be that they are rehearsed less often than small numbers, since they appear less frequently in textbooks and everyday situations (Hamann & Ashcraft, 1986).

However, although these factors are evident in childhood there is no evidence that they affect adult performance (Campbell & Oliphant, 1992). An alternative position is that numbers are represented internally or psychophysically by a mental number line that is compressed at one end, such that large numbers are more difficult to discriminate from each other. According to this interpretation, the activation of large numbers also activates neighbouring large numbers, which are more similar in magnitude than small numbers are to each other because of the compression of the visuo-spatial number line. Therefore, large problems encounter more interference from neighbouring numbers and are more susceptible to retrieval errors (Campbell & Oliphant, 1992). In this way, the magnitude of a number directly affects its retrieval difficulty.

2.7.6 Automatic properties of arithmetic

The problem-size effect has been used as a measure of the automaticity of arithmetic processes (Ashcraft et al., 1992), and therefore also (since automatic arithmetic is considered to be mediated by retrieval) as an indicator of retrieval-based versus computationally-based processing (Groen & Parkman, 1972; Logan, 1988).

Adult arithmetic shows evidence of obligatory memory retrieval, one of the properties of automaticity (Logan, 1988a). LeFevre, Bisanz & Mrkonjic (1987) used a task in which subjects were presented with two target numbers and were then shown a probe digit and were asked whether the probe matched either one of the two targets. Trials in which the probe digit was the sum of the two previous targets were rejected more slowly than neutral probes, suggesting that the target digits triggered an
obligatory activation of the addition fact in memory (their sum), despite the intention only to compare the probe and targets.

Further evidence of obligatory retrieval comes from the previously mentioned priming studies showing costs and benefits of performance associated with the triggering of activation of arithmetic facts in memory by a priming stimulus (Campbell, 1987; Zbrodoff & Logan, 1986; 1990; Stazyk et al, 1982; Ashcraft et al, 1992; Miller, Perlmutter & Keating, 1984; Campbell & Tarling, 1996)

2.7.7 Non-automatic properties of arithmetic

Adult arithmetic also shows evidence of properties typically associated with conscious, controlled processing. Zbrodoff & Logan (1986) found that a stop signal that interrupted performance of certain problems led to lower recognition rates for those problems at a later stage, compared with uninterrupted trials, indicating that arithmetic processing is not automatic. It may begin automatically, but requires intention for completion, and intention may be considered to place a load on working memory (Ashcraft et al., 1992).

Similarly, the persistence of the problem-size effect in retrieval-based adult arithmetic suggests that arithmetic is not fully automatic, and that it involves conscious or strategic processes. Evidence for this comes from studies using priming in arithmetic production and verification tasks and showing that facilitation due to correct priming is dependent upon problem difficulty (Ashcraft et al., 1992, p.326). For a multiplication verification task, low and medium difficulty problems were influenced at short (200 & 400ms) Stimulus Onset Asynchrony’s (SOA’s), suggesting automatic processing, whilst difficult problems were only facilitated at the longest SOA (1000ms), suggesting a possible role for conscious processing (p.321-324, Ashcraft et al., 1992). Koshmider & Ashcraft (1991) found similar results showing facilitation by correct primes at short SOA’s, whilst high difficulty problems only showed benefits at longer SOA’s (450 & 1000ms), suggesting that automaticity is dependent upon problem difficulty.
2.7.8 Automaticity of small, single-digit addition problems

Despite evidence suggesting that arithmetic is not completely automatic, the fact that a problem-difficulty effect exists (i.e., smaller problems produce faster and less error prone performance than large problems), and that smaller arithmetic facts are less affected by competition for working memory resources (Ashcraft et al., 1992) is suggestive of a greater level of automaticity for small problems. Consistent with this is evidence that a high degree of automaticity can be developed rapidly for an analogue of number arithmetic involving addends 2 to 5 (Logan, 1988a; Logan & Klapp, 1991; Klapp, Boches, Trabert & Logan, 1991). Although it is possible that automaticity for arithmetic involving small numbers may be due to their greater frequency of encounter in school texts (Hamann & Ashcraft, 1986) and in natural settings (Dehaene & Mehler, 1991, cited in Ashcraft et al., 1992), it is suggested that it is the ‘easiness’ of small arithmetic facts, due to easier discriminability of their internal representations (Campbell & Oliphant, 1992) that makes automaticity possible (Ashcraft et al., 1992).

2.8 Neurophysiology of automaticity

There appears to be a large body of work investigating automatized processing in the modalities of vision and audition, and even the somatosensory system, which utilize a varying number of techniques including event-related potentials (ERP’s), magnetoencephalography (MEG), and measurement of regional cerebral bloodflow with positron emission tomography (PET) (Naataanen, 1992). However, the majority of these studies are concerned with the processes and underlying brain mechanisms of attention selection and attention switching, both of which are pre-attentive processes (Naataanen, 1992). Nonetheless, there have been a number of studies that have investigated changes in brain activity associated with automaticity developed through extended practice.

2.8.1 Effects of extended practice on brain activity

Casini & Macar (1996) found evidence suggestive of reduced frontal activity after extended practice on a temporal (time-judgment) task. The prefrontal cortex has been implicated in the processing of time intervals (Fuster, 1981), and such temporal
Automaticity tasks demand that a high level of attention be maintained for the duration of performance. Similarly, early or novice task performance also requires high levels of attention (Shiffrin & Schneider, 1977; Posner & Snyder, 1975; LaBerge & Samuels, 1974). Casini & Macar (1996) found that after extensive practice, the right prefrontal region, which has been shown to be involved in sustained attention (Pardo, Fox & Raichle, 1991), was active during incorrect responses but relatively inactive for correct responses. They suggested that the reduced prefrontal activity seen for correct responses to the task may reflect more economical and more efficient use of neural resources, whilst greater activity for the incorrect responses may reflect the use of attention demanding and less efficient, more effortful processes.

Dale, Halgren, Lewine, Buckner, Paulson, Marinkovic & Rosen (1997) examined the effects of repetition using simultaneous functional magnetic resonance imaging (fMRI) and MEG. Subjects were presented with words (names of animals and objects) and had to make a button press response if the animal or object was more than a foot long. Compared to the repeated condition, the novel condition showed predominantly left hemisphere activation of the occipital-temporal junction (area 37), intraparietal sulcus (including the superior angular and supramarginal gyri) and posterior-ventral prefrontal cortex. However, for the repeated condition, all three areas showed reduced activity to the repeated stimuli beginning at least 350ms prior to the button press response.

Kopelman, Stevens, Foli, & Grasby (1998) found a significant correlation between regional cerebral bloodflow (rCBF) and free-recall in left medial temporal cortex, plus increased rCBF in right superior frontal cortex for the repeated-minus-novel condition for 15 words repeated over five consecutive blocks. Novel words (presented across three different lists) showed activation in the left inferior frontal and precentral gyri. They suggested that the left prefrontal activation in the novel condition may be a result of attentional resources, whereas left medial temporal activation may be associated with retrieval of items from episodic memory.

An FDG (fluorodeoxyglucose) positron emission tomography study by Haier, Siegel, MacLachlan, Soderling, Lottenberg & Buchsbaum (1992) examined changes in cerebral glucose metabolic uptake with the learning of a complex visuo-spatial/motor task (the computer game Tetris). Although there were no significant correlations between glucose metabolic rate (GMR) and task performance (Tetris score), certain areas showed significant differences (relative to the average GMR of
the brain slice containing that area) between the practiced and non-practiced conditions. Decreases in relative GMR were found in the left superior frontal cortex, left anterior cingulate, right posterior cingulate gyrus, left anterior and middle cerebellar cortex and the right posterior cerebellar cortex, whilst increases were found in the right pre-central frontal cortex, right hippocampus and left cingulate gyrus. Also, a significant decrease in overall brain glucose metabolism following practice was observed, leading the authors to propose that the subjects may have initially been using a variety of strategies involving many brain areas and then, after practice, decided on one set strategy which required fewer brain circuits or neurons (less brain activity), and therefore generated a lower glucose metabolism.

Carr (1992) reviewed PET findings of practice-related changes in brain activity for verb-generating and passive reading tasks within the framework of a proposed model of the human attention system involving two anatomically separate areas proposed by Posner & Petersen (1990); the anterior attentional system (AAS) and the posterior attentional system (PAS). Tasks requiring involvement of these structures are suggested to be attended or controlled, whilst those not requiring involvement of these structures are automatic (Carr, 1992, pp.225-226).

Carr’s (1992) meta-investigation of the automaticity of word recognition suggests two aspects of word recognition may rely on these two different neural structures that are “thought to serve the selective functions of attention” (p.225). Orthographic analysis appears to involve and be attended by the posterior attentional system (PAS), whilst semantic encoding tends to activate part of the AAS, and therefore appears to involve a different attentional network to orthographic analysis. Whilst both component processes of word recognition appear to require some degree of attentional involvement, they show differing patterns of “attentional dependency” (p.226), an idea consistent with the view that automaticity is a continuous dimension and not a dichotomy.

Part of Carr’s (1992) review looked at a study by Petersen, Fox, Mintun & Raichle (1989) which found that two areas within the anterior attentional system were active during a verb-generation task. Activity in the anterior cingulate gyrus and left inferior pre-frontal cortex was seen to diminish with practice at the task, whilst no activity was seen in these areas for the passive reading task. The AAS was proposed to possibly have the correct anatomical connections to enable it to serve an executive controlling function, “functions commonly attributed to ‘working memory’ ” (p.212,
Carr, 1992). As such, the high initial activity observed was suggested to denote AAS control of the task, whilst a decrease in activity was suggested to reflect a reduction in the need for AAS control “as if practice has turned the generate-verbs task from a novel semantic problem-solving activity requiring control by AAS to a restructured and more routinized skill - ie. an automatic one” (p.224) (Carr, 1992).

A similar reduction in activity with practice was observed in a PET study of verbal responses to visually presented nouns which revealed changes in blood flow in two separate cortical areas (Raichle, Fiez, Videen, MacLeod, Pardo, Fox & Petersen, 1994). Subjects were asked to verbally repeat visually presented nouns (repeat nouns task) and then were asked to generate appropriate verbs for the nouns as each noun was presented (generate-verb task - naive condition). Subjects were given further practice on the generate verbs task with the same list of words (practiced condition). Later, they performed the generate-verb task on a second word list (novel condition).

The naive condition showed increased blood flow to the anterior cingulate, left prefrontal cortex and right cerebellar cortex. However, in the practiced condition, activation in these areas was decreased, but increased in the sylvian-insular cortices bilaterally, and this pattern of activation was indistinguishable from the simple repeat nouns task. The sylvian-insular cortices appear to be active in word repetition, a relatively automatic process with minimal semantic processing, and also after practice on the generate-verb task, when responses tend to become stereotyped (a consistent stimulus-response mapping begins to develop).

The introduction of the second word list (novel condition) led to reactivation of the left frontal and anterior cingulate cortices and also the right cerebellar hemisphere, as well as a deactivation of the left sylvian-insular cortex (Raichle et al., 1994).

The authors propose that two separate neural pathways are utilized in the generating of verbs; the first pathway is made up of the anterior cingulate, left prefrontal cortex and right cerebellar hemisphere (active in the naive and novel conditions), and is used when there has been little or no practice on the task and responses are less automatic. The second pathway involves the sylvian-insular cortices and left medial extrastriate cortex, which is active in the practiced condition, when responses are stereotyped and more automatic.

Decreased blood flow in the right cerebellar cortex accompanying decreases in response time with practice was suggested to be indicative of item-specific
learning. Consistent with this, paramedian cerebellum, primary motor cortex and supplementary motor area (all associated with motoric aspects of speech production) showed no significant changes in blood flow with practice, leading the authors to postulate that subjects were learning to respond specifically to individual nouns, rather than just learning how to say the responses (generalized learning). The similarity of activation in the naive and novel conditions (when new responses to new stimuli are being learned) further supports this position, and is consonant with ideas of item-based learning expounded by automaticity-as-memory theories. Process-based learning would predict that the novel condition constituted further practice on a relatively automatic task, and as such, the second (automatic) pathway should be active. The results, however, showed that the first pathway was reactivated by the novel word list (Raichle et al., 1994).

The idea of separate neural areas governing performance of routinized and novel behaviour is carried further by Goldberg, Podell & Lovell (1994). A review of tachistoscopic and dichotic task performance revealed that task-naive subjects showed a right hemisphere advantage whilst task-experienced subjects showed a left hemisphere advantage for a number of non-verbal tasks. Also, a right hemisphere advantage was seen in early blocks of trials for novel tachistoscopic non-verbal tasks whilst a left hemisphere advantage was found for later blocks.

These and similar results seem to indicate a right to left hemisphere shift of control in cognitive learning and led the authors to propose that the hemispheres may have affinities for certain functions, suggesting that “the right hemisphere is critical for the exploratory processing of novel cognitive situations to which none of the codes or strategies pre-existing in the subject’s cognitive repertoire applies” and “the left hemisphere is critical for processing based on pre-existing representations and routinized cognitive strategies” (p.372, Goldberg, Podell & Lovell, 1994).

2.8.2 Arithmetic and brain activity

A number of studies have implicated certain brain regions as being associated with arithmetic performance, most notably bilateral parietal areas (see Dehaene, Dehaene-Lambertz & Cohen, 1998).

Roland & Friberg (1985) found increased rCBF (greater in the right hemisphere) in bilateral superior frontal cortex, anterior mid-frontal cortex, angular
cortex and Broca's area for an arithmetic task involving counting backwards from a given number by three's. Inouye, Shinosaki, Iyama & Matsumoto (1993), using an EEG 'irregularity index' and an 'information flow' measure, found greater activation of the left temporo-centro-parietal region during an arithmetic task (serial subtraction of 7 from 1000) compared to a resting state. Activation of the mid-frontal region was also associated with the arithmetic task, and it was interpreted as "non-specific activation common to various mental tasks" (p.229), but was nevertheless thought to play an important role in arithmetic performance.

Ruchkin, Johnson, Cahoune & Ritter (1991) used complicated mathematical tasks (divide a 3-digit number by 7 and compute the remainder, add the first two digits of 3-digit number then subtract the third digit from that sum). They found a pre-frontal positivity during the period of time between stimulus presentation and response, which they associated with allocation of resources or coordination of processing, and a centro-parietal negative slow wave "immediately preceding and synchronized to the response time" (p.484), which they associated with deliberate calculation procedures.

There have been few studies investigating the relationship between brain activity and practice on mental arithmetic tasks, but two studies have shown evidence of changes in the localization of brain activity with practice. Pauli, Lutzenberger, Rau, Birbaumer, Rickard, Yaroush & Bourne (1994) and Pauli, Lutzenberger, Birbaumer, Rickard & Bourne (1996) found a decrease in frontal activation with extensive practice, and evidence suggesting parietal involvement in arithmetic.

After extended practice, the amplitude of a late positive wave occurring approximately 300ms after stimulus presentation was found to decrease in frontal and central regions whilst parietal amplitude was not significantly altered. The frontal activity was suggested as being associated with deliberate calculation (multiplication), and the amplitude decrease with practice was suggested to reflect an increase in memory retrieval processes (and a decrease in calculation processes), based on the assumption of a shift with practice from effortful calculation to fast retrieval of solutions from memory (Pauli et al., 1994). However, for a similar multiplication task, Pauli et al. (1996) found that frontal amplitude of this late positive component did not show problem-difficulty or practice specificity effects, and suggested instead that it reflected "general information processing…not specifically related to mental arithmetic" (p.528). Since parietal amplitude of the positive slow wave was not
affected by practice, it was suggested that this region was "functionally necessary to answer retrieval" (p.27, Pauli et al., 1994).

Pauli et al. (1994) found that pre-response amplitude of a slow wave following the late positive component was mostly negative. The pre-response amplitude in parietal regions was found to be significantly higher for moderate and difficult tasks compared to easy tasks, and similarly to the late positive wave, also decreased with practice. Given that parietal negativity appears to reflect calculation processes associated with the use of complex mathematical tasks (Ruchkin et al., 1991), the negativity was suggested to reflect the use of calculation strategies, and the decreased negativity with practice was taken as evidence of a reduction in the use of such strategies (Pauli et al., 1994).

However, Pauli et al. (1996) found that parietal pre-response amplitude was mostly positive and "became more positive with practice and less positive with increasing problem-difficulty" (p.528). Consistent with the findings of the earlier study, this parietal pre-response positivity (Pauli et al., 1996) was interpreted as reflecting memory retrieval processes, whilst the negativity of the earlier study was suggested to be due to insufficient training failing to produce memory retrieval processes (Pauli et al., 1994).

2.8.3 Summary of neurophysiological changes with automatization

For a wide variety of tasks, including judgments about words and time intervals, verb generation, arithmetic, and perceptual-motor tasks, there appears to be a general reduction in frontal activity with practice. Areas that show such reductions include frontal and prefrontal cortex and also anterior cingulate, which has connections to prefrontal cortex (Goldman-Rakic, 1987) and has been suggested to be part of an anterior attentional system (Posner & Petersen, 1990). The reliability of these decreases in brain activity is suggested by the fact that they have been observed using a range of neurophysiological measures including glucose metabolism, regional cerebral blood flow and electroencephalography.

Automatization also appears to involve the cerebellum, reflected in a reduction in cerebellar activation with practice, not just for motor tasks (i.e., Haier et al., 1992), but also for cognitive tasks such as verb generation (Raichle et al., 1994).
Such activation (of the right cerebellar cortex) has been suggested as reflecting item-specific learning (Raichle et al., 1994),

Performance of arithmetic tasks appears to involve frontal and parietal brain regions. However, similarly to changes which other tasks undergo with practice and automatization, arithmetic (multiplication) shows decreased activation in frontal regions, whilst a lack of change in parietal activity is suggested as reflecting this region's necessity in accessing arithmetic number facts during both novel and practiced performance (Pauli et al., 1996).

2.9 Conclusion of Literature Review

The formation of habit or the development of automatization is associated with a diminishment of conscious attention, a simplification of movement and an increase in speed of performance and accuracy (James, 1890). Skills are made up of numbers of smaller component skills which become automatized during the process of learning (Fitts, 1964), and performance after extended practice becomes faster, following a power law (Crosman, 1959; deJong, 1967). However, expert performance is not simply more automatic than novice performance; experts also use different strategies and have more knowledge about their given area of expertise than novices (Chi, Glaser & Rees, 1981).

To view automaticity as a dichotomy between automatic and controlled processes does not appear to be appropriate since automatic processes have been found to be highly controlled (Logan, 1982; Levelt, 1983). Just as skill is a continuum, the degree of automaticity of a process also lies along a continuum (Logan, 1985b; Logan, 1988a; Cohen, Dunbar & McClelland, 1990), with some individuals or performance of particular skills being less or more automatic than others (Logan, 1985b).

The two-process view of automatization proposes that practice reduces the capacity that a particular process requires or draws from the finite pool of resources available to the information processing system (Hasher & Zacks, 1979; Logan, 1979; LaBerge, 1973), but no mechanism explaining how this occurs has been advanced (Logan, 1988b).

Alternatively, the memory view of automatization sees the development of automaticity as a build up of information in memory (Anderson, 1982; Logan, 1988a;
Automaticity

Logan, 1988b), a position consistent with evidence that compared to novices, experts have greater knowledge of a given domain and superior organization of that knowledge (Chi, Glaser & Rees, 1981).

The memory view can account for improvements in arithmetic with practice, seeing the development of automaticity as a transition from counting to memory retrieval of arithmetic facts (Logan, 1988a; Logan & Klapp, 1991), and this conceptualization concurs with models of the development of arithmetic skill in children (Groen & Parkman, 1972).

Imaging studies of the effects of extended practice on brain activity suggest an overall picture of a reduction in brain activity in frontal and prefrontal regions (Haier et al, 1989; Petersen, Fox, Mintun & Raichle, 1992; Raichle et al, 1994; Casini & Macar, 1996), and this also appears to be the case for extended practice on arithmetic tasks (Pauli et al., 1994; Pauli et al., 1996).

Although simple arithmetic processing does not appear to be fully automatic, it is apparent that a higher degree of automaticity for small numbers exists in number arithmetic (Ashcraft et al, 1992), and can be developed rapidly in an analogue of number arithmetic (Logan, 1988a; Logan & Klapp, 1991; Klapp, Boches, Trabert & Logan, 1991). Accordingly, this study has been designed with a view to monitoring brain electrical activity during the process of automatization of such an analogue task (Alphabet Arithmetic).
Introduction to Alphabet Arithmetic and Steady-State Probe Topography

This chapter will serve to elaborate on the research approach taken for this thesis, and will necessarily involve an overview of the Alphabet Arithmetic activation task (Section 3.1), and the methodology and terminology of evoked potential techniques in order to orient the reader (Section 3.2). This will be followed by an introduction to probe evoked potentials and steady-state evoked potentials (Section 3.3). Finally, in Section 3.4, an overview of the Steady-State Probe Topography (SSPT) technique and relevant SSPT findings will be made with a view to familiarizing the reader with the interpretation of SSPT data and in order to lay the foundations for the hypothesis of this study.

3.1 Alphabet arithmetic

In order to document changes in brain electrical activity with automatization, a task that could be relatively rapidly automatized (within one experimental recording session) was required. Alphabet Arithmetic fitted this criterion since previous studies have shown that small sets of Alphabet Arithmetic facts have been able to be automatized within fifteen minutes (Logan & Klapp, 1991), and individual facts within larger sets have been automatized with as few as 70 repetitions (Logan, 1988a).

Number addition was unsuitable for such a task because although it shows a transition from counting to memory retrieval, this transition takes place when children are at a relatively early stage in their schooling, and there is little left to be learnt in the domain of single-digit addition by the time adulthood is reached (Logan & Klapp, 1991). Also, apart from the practical and ethical difficulties in controlling for levels of practice of single-digit number addition in individuals, it is more desirable to use adult subjects to investigate the transition from counting to remembering because of the variability and slowness of response times in children (Logan & Klapp, 1991).
Compared to number arithmetic, Alphabet Arithmetic can be assumed to be a relatively novel task for most adults, allowing experience with the task to be closely controlled, whilst still ensuring that subjects possess enough knowledge to be able to manipulate the task information correctly (i.e. they know the sequence of the alphabet and numerical system, and know how to count). The combinations of the two skills (counting and reciting the alphabet) acts as “an analogue of the acquisition of addition skills in children and allows adults to perform as novices in the task domain” (Compton & Logan, 1991, p.152).

The task used in this study was a derivation of the alphabet arithmetic task used by Logan (1988a; Logan & Klapp, 1991; Klapp, Boches, Trabert & Logan, 1991). The stimuli were equations of the form B + 3 = E, in which a number (addend) is added to a letter to form the answer, another letter. In some cases, the equation was true; that is, the answer was equal to the sum of the letter plus the addend, but in others, the equation was false, with the answer being one letter further along the alphabet from the correct answer (+1 condition; i.e. B + 3 = F) or one letter back from the correct answer ( -1 condition; i.e. B + 3 = D).

As in the case of single-digit addition, response time data for Alphabet Arithmetic has revealed a 400-500ms increase in response time for each increment of the addend, and is thought to reflect the use of a counting algorithm (Logan, 1988a; Logan & Klapp, 1991). After extended practice, performance of the task using memory recall has also been readily identified in the response time data as a zero slope in the relation between response time and digit addend. That is, there is no linear increase in response time as the addend increments; response time is relatively constant for all addends because the ability to memorize or recall an answer to an equation is not dependent upon the magnitude of the digit addend (Logan & Klapp, 1991). Similarly to single-digit addition, the process of automatization of Alphabet Arithmetic will therefore be reflected as a transition from counting to memory retrieval. After extended practice, memory-based performance will be faster than performance based on the counting algorithm, but subjects will only switch to the memory process when it is faster and more reliable than the algorithm. Thus, as for single-digit addition, the process of automatization of Alphabet Arithmetic will be reflected in the data as a reduction in response time according to a power law, and a reduction in the slope of the function relating response time with the magnitude of the addend.

3.2 Evoked potentials

Much work on automatization has concentrated on pre-attentive automatic processes (see Naataanen, 1990) rather than on automatic processes developed through extended practice. Those studies that have focused on the effects of extended practice have tended to use methodologies with relatively low temporal resolution, such as measurement of rCBF using PET (Haier et al., 1992; Carr, 1992; Raichle et al., 1994). However, the nature of cognition, especially that associated with fast, automatic processes, requires a methodology with high temporal resolution to document rapid changes in brain activity that could potentially occur even over a short period of practice (see Raichle et al., 1994).

Evoked potentials (EP’s) require the utilization of consistent, short, discrete, stimuli in order to elicit responses which are assumed to be relatively invariant because of the identical nature of the stimuli (Silberstein et al, 1990). High temporal resolution investigations of automatic processes have been undertaken utilizing transient evoked potentials (Hoffman, Nelson & Houck, 1983; Strayer & Kramer, 1990), but although it provides millisecond temporal resolution, hundreds or thousands of averages are required to obtain a satisfactory signal-to-noise ratio (Regan, 1982).

Given the rapid changes in response time and response time variability with repetition of a task (see Fitts, 1964; Newell & Rosenbloom, 1981; Crossman, 1959; Snoddy, 1926) and successive presentations of unique stimuli (Logan, 1988a; Logan & Klapp, 1991), it is not unlikely that rapid and significant changes in brain activity will also occur with repetition of a perceptual-motor or cognitive process (Pauli et al., 1996). As such, for investigations utilizing transient evoked potentials, the requirement of a large number of like responses makes it difficult to document the relatively small changes between successive stimuli that occur with learning (these small changes will be averaged together).
3.3 Probe evoked potentials

A further development in transient evoked potential methodology has been the use of probe EP’s involving the recording of brain responses to a well-defined, repetitive, but irrelevant stimulus whilst a cognitive task is undertaken. The premise of the recording paradigm is that the processing required by the task will “compromise the efficiency of neuronal systems in processing a concurrent irrelevant probe stimulus” (p. 108, Papanicolaou & Johnstone, 1984), thereby leading to variations in parameters such as amplitude or latency of the potentials evoked by the irrelevant stimulus, and more specifically, task-dependent amplitude attenuation and latency increases. Results supporting these assumptions (Johnstone, 1982; Papanicolaou & Johnstone, 1984) suggest that probe evoked potentials can provide a measure of the residual capacity during cognitive processing and as such, that it is a suitable method for investigating regional involvement of brain areas in cognitive task performance (Papanicolaou & Johnstone, 1984).

The majority of evoked potential studies have focused on transient EP’s (see Papanicolaou & Johnstone, 1984), whereby the visual system is allowed to return to its initial or resting state before the next stimulus is given. However, few studies have investigated the effects of cognition upon the potentials evoked by rapidly repeated stimuli, in particular visually-presented stimuli (Silberstein et al., 1990). These stimuli are delivered at a higher rate such that “the response to one stimulus has not died away before the next stimulus is delivered” (p.45, Regan, 1982), and are referred to as “steady-state” stimuli. The evoked potentials elicited by such stimuli are termed steady-state visual evoked potentials (SSVEP’s) and have been shown to correlate with cognitive processing.

Wilson & O’Donnell (1986) found that the apparent latency of a steady-state evoked response (seen as a lag in the response relative to the stimulus waveform) was correlated with scanning speed in the Sternberg memory task. They found that responses evoked by a high frequency visual flicker were correlated with the sensory-motor components of the task, whilst responses to a medium frequency visual flicker were correlated with cognitive portions of the task. Also, parietal latency showed a greater correlation with the mental rotations task data than with the simple reaction time data, suggesting the possibility of observing cortical specificity for differing cognitive processes (Wilson & O’Donnell, 1986).
However, a further study by Wilson & O’Donnell (1988) suggested that the SSVEP was insensitive to cognitive processes as measured by the correlation between SSVEP latency and mental workload. But Silberstein et al. (1990) suggest that methodological short-comings in the study, namely the measurement of SSVEP at only two central sites (Oz & Pz), and the consideration of latency only (and not amplitude), limit the applicability of the findings in extrapolating the effects of cognitive processes on the SSVEP.

For this technique, in order to make interpretations about changes in brain activity associated with a task, it is assumed that increases in brain activity will be associated with attenuation of the probe-SSVEP, just as it is for probe-EP’s. Such attenuation is suggested to be caused by competition for cognitive resources in simultaneously processing both the probe stimulus and the cognitive task itself. As more resources are utilized in performing the cognitive task, fewer resources are available to process the probe stimulus, thereby attenuating the signal evoked by the probe (Papanicolau et al., 1987). This phenomenon is similar to the transient reductions in alpha amplitude labeled “event-related desynchronisation” (ERD) which are associated with cognitive or motor task performance (Pfurtscheller & Aranibar, 1977; Pfurtscheller & Klimesch, 1990).

### 3.4 Steady-state probe topography (SSPT)

A number of other studies have shown attenuation of probe-EP’s in brain regions thought to be associated with performance of certain cognitive tasks. A technique developed at the Brain Sciences Institute termed Steady-State Probe Topography is a combination of the probe-EP and steady-state event-related potential methodologies. It utilizes the SSVEP and involves using a probe or task-irrelevant stimulus (a visual flicker), and then observing the changes in amplitude and phase of the potentials evoked by that probe stimulus as a cognitive task is undertaken (Silberstein et al., 1990).

For a vigilance task involving viewing of a series of geometric shapes (circles and squares), Silberstein et al. (1990) found an overall reduction in the SSVEP amplitude for the third trial of the task which required subjects to identify a modification to one of the shapes (a circle). This third trial of the task was characterized as an active viewing task involving increased attentiveness, and the
attenuation of the SSVEP in occipital-parietal, parietal-central and right frontal areas was suggested to be indicative of increased brain activity (relative to Trial 2) at these sites. In particular, increased occipital activity during anticipation and target detection (inferred from occipital SSVEP attenuation) was consistent with indications of increased occipital/parietal rCBF being correlated with increased visual attention. (Roland, 1984; Mazziotti & Phelps, 1984,).

The same group (Silberstein et al., 1995) has also investigated changes in SSVEP topography associated with performance of the Wisconsin Card Sort test, which requires subjects to sort stimuli by three categories - number, shape or colour. The sort criterion was maintained for ten successive presentations of the stimuli but was then changed without the subject’s knowledge on the eleventh presentation, requiring the subject to select a new criterion by which to sort or group the succeeding stimuli. Compared to the fifth presentation, when an established sort criterion merely had to be re-applied to the presented stimulus, there was a marked attenuation of the SSVEP amplitude in pre-frontal, centro-parietal and right temporal regions for the eleventh presentation (which required a criterion change). The surge of activity (inferred from the SSVEP attenuation) at Card 11 occurred at the time at which the subjects needed to evaluate the feedback and determine a new criterion by which to sort the stimuli. This inferred increased prefrontal activation is consistent with ideas of the involvement of this region in changing sort criterion, suggested by neuropsychological evidence that damage to prefrontal regions is associated with impairment of ability to utilize feedback indicating a need to change the sort criterion (Milner, 1963). Further SSVEP attenuation in the right parieto-temporal region at Card 11 was suggested to reflect increased demands on recognition memory as subjects maintained a representation of the old criterion and selected a new criterion (Silberstein et al., 1995).

A further study by this group has also investigated changes in SSVEP amplitude and latency associated with the AX-version of the continuous performance task. Subjects had to respond to the target letter “X” only if it was preceded by an “A”. Frontal SSVEP amplitude experienced a transient decrease at presentation of the X, suggesting an increase in brain activity frontally. Simultaneously, a transient increase in SSVEP amplitude occurred parieto-occipitally, suggesting a decrease in activity in parieto-occipital regions. This was inferred to reflect “a transient reduction in vigilance following detection of a visual target” (Silberstein et al., 1996, p.382),
which is consistent with the view that the parieto-occipital region plays a central role in mediating visual attention (Silberstein et al., 1996).

Latency of the SSVEP also appeared to serve as an indicator of cortical excitation, in that differences in the latency of the SSVEP were found to be associated with differences in reaction time. Compared with slower trials, fast trials were associated with a reduced latency of the SSVEP at prefrontal sites. Given the similarities in the SSVEP amplitude for fast and slow trials, these latency differences suggest that different aspects of cortical excitation may be indexed by SSVEP amplitude and latency (Silberstein et al., 1996).

3.4.1 SSPT suitability

In summary, the Steady-State Probe Topography technique appears to be well suited to the measurement of brain activity associated with rapid cognitive processing. Whilst PET offers high spatial resolution, the low temporal resolution (from about one minute upwards) does not allow a distinction between uniform or transient activation within that minimum time-frame (Silberstein et al., 1995). Alternately, transient evoked potentials provide millisecond resolution, but the requirement of invariance of evoked potential characteristics makes it unsuitable to investigate processes that show changes with practice. On the other hand, the Steady-State Probe Topography technique provides a measure of rapidly changing brain processes in a continuous fashion and with a relatively high temporal resolution (seconds) (Silberstein et al., 1990). Also, such high temporal resolution allows the cognitive components of each trial of a task to be separated from the perceptual and motor components of that trial. As such, the Steady-State Probe Topography technique would seem to be an appropriate methodology to study ongoing changes in brain activity that are presumed to occur during learning.

3.4.2 Distinction between 'intake' and 'rejection' tasks

The view that the alpha rhythm indexes low brain activity, often being referred to as an "idling rhythm", (Pfurtscheller, 1992; Pfurtscheller & Klimesch, 1990; Van Winsum, Sergeant, & Geuze, 1984), originated in early observations of attenuation or 'blocking' of alpha activity associated with information processing and
movement (Pfurtscheller & Klimesch, 1990). More recent work has suggested that this view may be an over-simplification, since a number of findings have indicated that in the frequency range under consideration (8-13Hz), certain tasks will be associated with increased alpha amplitude.

Ray & Cole (1985) found that parietal alpha band activity increased when subjects attended to internal information. Ray & Cole (1985) used a number of left and right hemisphere tasks that were categorised as being intake (counting verbs in a passage, choosing the correct representation of a geometric figure) or rejection tasks (mental arithmetic, mental rotation of a three-dimensional object), and found that alpha levels for rejection tasks were greater than alpha levels for intake tasks. This finding outlines a distinction which can be made between tasks requiring attention to, and processing of, external information (intake or perceptual tasks), and those requiring rejection of external events in order to attend and manipulate internal information (rejection or working memory tasks).

Other supporting evidence for increases in amplitude of the 8-13Hz frequency range during rejection tasks comes from an MEG study showing increased alpha activity during the visualization of self-performance of motor activity (Tesche, Uusitalo, Ilmoniemi & Kajola, 1995), and increased alpha for the memorization portion of an auditory memory task in which subjects had to decide whether a probe letter belonged to a previously presented memory set of vowels (Krause, Lang, Laine, Kuusisto & Porn, 1996). Consistent with these results, Vogt, Klimesch & Doppelmayr (1998) found increased power in the 10-12Hz alpha-band associated with the memorization of words. Accordingly, the interpretation of the attenuation of alpha as an increase in activity may only apply to 'intake' tasks.

The distinction between 'intake' and 'rejection' tasks has also been observed in the SSVEP, including the previously mentioned SSPT studies which utilised 'intake' tasks. For example, Silberstein et al. (1990) found a decrease in SSVEP amplitude occipito-parietally for a visual vigilance task requiring subjects to view a series of geometric shapes (circles and squares) and identify a circle which had been modified, whilst for an AX version of the continuous performance task (CPT), presentation of the ‘A’ and ‘X’ was associated with attenuation of SSVEP amplitude frontally (Silberstein et al., 1996). On the other hand, for a working memory task, retention (in which subjects had to remember the spatial location of three dots) was associated with an increase in SSVEP amplitude in frontal and parietal regions (Silberstein et al.,
An equally important aspect of this study was the finding of a decrease in the latency of the SSVEP in frontal and parietal regions during the retention interval, which in concert with the amplitude increase, is suggested to reflect increased excitation, consistent with a theory of neocortical dynamics proposed by Silberstein (1995a; 1995b; 1997; 1998).

Given that Alphabet Arithmetic would appear to involve a strong working memory component, in that (at least initially) the task will involve counting and the internal manipulation of the elements of each equation (the letter and the addend), these findings suggest a more appropriate way of interpreting the SSVEP data, and provide a model by which the results of this study may be understood.

3.5 Conclusions and hypothesis of this study

The objective of this study was to investigate the process of automatization by observing the differences in brain electrical activity between a novel, unpracticed task and a well-practiced, automatized task. Within the framework of the dichotomy between controlled and automatic processing, and the effects of extended practice on the transition from conscious, effortful, non-automatic processing to fast, effortless, automatic processing, the initial (Algorithmic) task was designed to maximize the need to use an effortful counting process. On the other hand, the Automatization sessions were designed to allow for rapid learning of stimulus-response associations and for the development of automatic responses to those stimuli after extended practice (by the fifth session, A5).

Taking into consideration the nature of Alphabet Arithmetic (a 'rejection' task), it is hypothesized that initial performance will show a similar SSVEP response pattern to that previously found for a working memory task (Silberstein, 1997), namely an amplitude increase and latency decrease. Additionally, given the apparent involvement of parietal regions in performance of arithmetic tasks (Ruchkin et al., 1991; Pauli et al., 1994; 1996; Dehaene et al., 1998), increased SSVEP amplitude and decreased latency (suggestive of increased excitation) in these regions is also expected to be observed at all levels of practice.

Regarding automatization, reductions in frontal activity with practice observed in other studies of automatization (e.g., Haier et al., 1992, Raichle et al., 1994, Pauli et al., 1994; 1996) suggest the possibility of a similar pattern of activity in
this study. Therefore, it is hypothesized that automatization of the alphabet arithmetic task will be associated with a reduction in frontal excitation, reflected in a decrease in SSVEP amplitude and an increase in latency with practice.

Specifically, it is hypothesized that the Algorithmic task will be characterised by increased SSVEP amplitude and decreased latency in frontal regions, whilst the Automatization task (A5) will be characterised by decreased SSVEP amplitude and increased latency frontally.
Chapter 4

**Method**

The previous chapter introduced and provided the rationale for the use of both the alphabet arithmetic task and the steady state probe topography technique in investigating rapid and significant improvements in task performance with practice.

The aim of this chapter is to document the materials and techniques used to carry out this study. Section 4.1 will provide a description of the subject pool, followed by a short discussion of a preliminary trial of the task and considerations in the modification of the task to suit the needs of the project, as well as a description of the physical nature of the Alphabet Arithmetic stimuli and the structure of the task. Section 4.2 will describe the experimental procedure, the location of electrode sites, and the recording technique, followed by a description of the nature of the evoked potential eliciting stimulus. Section 4.3 details methods for artifact detection and normalization of data, plus processes for averaging of SSVEP data across trials and subjects. Section 4.4 describes techniques used for topographic mapping of the SSVEP amplitude and latency components, and the statistical differences between practiced and non-practiced performance.

4.1 Experimental design

4.1.1 Subject pool

Subjects for this study were thirty-seven 1st, 2nd and 3rd year university students, some of whom had completed other tertiary qualifications at an earlier stage of education. From this total pool of 37 subjects, eight were excluded because of corrupted or poor quality electrophysiological data and a further five were excluded on the basis of poor task performance, as reflected in their response time data. The results of this study are based on the behavioural and electrophysiological data of the remaining 24 subjects.

This group consisted of eleven males and thirteen females with an age range of 18-31 years and a mean age of 21 years. Eighteen subjects were right-handed and
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six were left handed, as assessed by the Edinburgh inventory (Oldfield, 1971). All subjects were paid for their participation.

4.1.2 Preliminary evaluation of the Alphabet Arithmetic task

The development of automatization has been shown to depend upon the number of times each fact is encountered (Logan & Klapp, 1991). The Algorithmic block of trials was designed to limit processing to Algorithmic means (counting) and to prevent automatic processing based on memory retrieval. This was achieved by using a large number of different alphabet arithmetic equations or facts, which minimized the number of times each fact was presented.

Conversely, processing at the end of practice needed to be as automatic as possible, as this would provide the best opportunity for comparing automatic and non-automatic processing. To achieve this, the number of equations for the Automatization blocks was significantly reduced compared with the Algorithmic block, to allow for a large number of presentations of each equation within the relatively short time-period (about 45 minutes) envisaged for each recording session.

The task originally developed for this project utilized three letters (H, N & T) and two addends (3 & 4), producing six True equations with two incorrect (False) equations being generated for each True equation, providing a total of 18 separate facts. A preliminary investigation of the efficacy of this task structure using the response time data of twelve subjects revealed that the three letter/two addend combination was too difficult for most subjects to develop automatic responses to the equations, due to the short time frame available to perform the task, and the relatively low number of presentations of individual stimuli. Therefore, it was decided to reduce the amount of information required to be learnt by removing the “N” equations, leaving twelve true and false facts. This also had the effect of further increasing the number of times each individual stimulus was presented.

An extra block of trials was also added and so the overall task time was slightly lengthened. This had the effect of providing more time for the subject to learn the task and allowed an extra rest period. The extra rest period was designed to help prevent fatigue and boredom for the subject, which could develop because of the tendency of the electrode helmet and SSVEP stimulus to become uncomfortable, and because of the high level of concentration that the task required.
4.1.3 Stimuli

The Alphabet Arithmetic equations and associated feedback were coloured white and were presented in Times New Roman font on a black background in the centre of the computer monitor. The equations and feedback were 23mm high × 86-108mm long, and subtended a vertical angle of 1° 05’ and a horizontal angle between 4° 34’ and 5° 09’ when viewed at a fixed distance of 120cm.

4.1.4 Task structure

The equations were presented in six separate blocks of trials, each of duration 6 minutes 10 seconds. Subjects performed as many trials as possible within this time-limit for each block.

The first (Algorithmic) block contained a large number of different equations which were produced by various combinations of 12 letters (F to S, excluding H & N) and two addends (3 & 4). This produced 24 true equations (12 letters × 2 addends) plus an additional 48 false equations - each correct equation had two false forms in which the product of the equation was one letter above (+1 condition) or one letter below (-1 condition) the correct answer. The equations were randomly arranged for presentation and the presentation order was identical for all subjects. To preserve the ratio of true to false equations and hence an equal ratio of “Yes” and “No” responses, each true equation (n=24) was individually presented twice as often as each false equation (n=48). This was done as a way of circumventing guessing or anticipation of answers, which might have occurred if the probabilities of true and false equations was unequal. For example, if there were twice as many false equations as true equations (Pr(Incorrect)=.66), subjects may have attempted to guess the response for the equations and would have been correct two-thirds of the time.

The combination of the large number of individual alphabet arithmetic facts (72) in the Algorithmic task block, and the short time period of the task (just over six minutes), meant that a relatively small number of trials were performed - the maximum was 116. On average, the number of times an individual equation was presented was twice, with a maximum of three times. In light of this, memorization of the correct stimulus-response pairing for any given equation would have been highly unlikely.
The Algorithmic block was designed to give the subject practice on the alphabet arithmetic task, allowing the subject to maximize their counting speed and to develop an efficient and consistent strategy to perform the task, rather than continuing to try out a number of alternative strategies during the succeeding Automatization blocks. By providing practice on the task but preventing automatization, the algorithmic session was designed to separate the effects of general learning (ie. developing an efficient strategy, maximizing counting speed, improvement of motor components) from automatization (ie. developing specific responses to specific stimuli), although a continuation of general learning of the task during the automatization sessions cannot be discounted as a source of improvement.

The remaining five (Automatization) blocks contained 12 different equations made up from combinations of two letters (H & T) and two addends (3 & 4) (see Figure 4.1).

![Figure 4.1](image)

Figure 4.1 Tree structure of the Alphabet Arithmetic task (Automatization Blocks). Equations can be broken up into two types of categories - True or False. Each category can be further split into letter categories (H or T) and then even further broken down into number or addend categories (3 or 4).

There were four true equations (\(H+3 = K; \ H+4 = L; \ T+3 = W; \ T+4 = X\)) and eight false equations (2 Letters \(\times\) 2 Addends \(\times\) 2 Conditions) in which the product was one letter above or one letter below the correct answer (e.g. \(T+4=W\), \(H+3=L\)). Similarly to the Algorithmic block, the True equations in the five Automatization blocks were presented twice as often as False equations.
There was a maximum possible total of 1440 trials across the five Automatization blocks, with the fastest subject completing 1047 of these. The relative brevity of the automatization period is evident when compared to Logan & Klapp (1991), in which subjects took 12hrs and 5760 trials to automatize forty alphabet arithmetic facts, and Logan (1988a) in which subjects performed 5760 trials in the process of learning 80 facts.

4.2 Experimental procedure

4.2.1 Task presentation

Subjects were seated in front of the computer monitor on which the alphabet arithmetic task was to be presented and prepared for electroencephalographic recording (attachment of reference and ground electrodes, positioning of electrode helmet). They were informed that the purpose of the experiment was to examine how various tasks or processes become second nature or automatic after extended practice, and that a task called Alphabet Arithmetic was going to be used to assess this.

Subjects were then shown an equation (the first equation of the practice block), and the format of the equations (i.e. letter + addend = product) was explained. The subjects were told that it was their task to determine whether each Alphabet Arithmetic equation was correct or incorrect, and they were shown how to perform the task by counting through the alphabet, using the first three equations from the practice block as examples. Instructions were given, asking subjects to respond as quickly as possible to the stimuli and were told that it did not matter if they made a mistake as long as they did not make too many. Whilst both speed and accuracy were stressed, subjects were told that speed was slightly more important than accuracy.

The practice block of 50 equations (letters F - S excluding H & N) was presented for the purpose of allowing the subject to become accustomed to performing the task as well as wearing the electrode helmet and SSVEP goggles. This block was not time-limited; all subjects worked through the full fifty equations and the time taken was dependent upon the speed of the subject.

After the practice block the instructions were re-iterated and then the Algorithmic block was presented (see Figure 4.2). Just before the Automatization blocks were presented, a further set of instructions was given, explaining that the
subject was now going to be presented with fewer variations of the alphabet arithmetic equations (compared to the Algorithmic block). Subjects were told that they would probably find that the task became easier and that they may eventually get to the stage whereby they would recognise an equation and know whether it was correct or incorrect without having to count through the alphabet.

Figure 4.2 Presentation order of alphabet arithmetic blocks. The practice task of 50 equations was presented first to allow subjects to familiarise themselves with the presentation sequence and making responses to the equations. The Algorithmic task was presented next and was designed to allow subjects to optimize their Alphabet Arithmetic counting. This was followed by the five Automatization blocks which were designed to allow for the development of consistent stimulus-response relations. Subjects worked through the practice session at their own pace and then ran through the Algorithmic and five Automatization blocks, which were all limited to the time required to record 300 sweeps of EEG data (approximately 6 mins 10 secs).

The five Automatization blocks were then presented in succession, with a short break of about one minute (during which the SSVEP stimulus was switched off) between each block to help prevent fatigue and boredom.

The subject’s responses were recorded from a two-choice button box, labelled Y (Yes) and N (No). A correct response by the subject occurred when he/she correctly identified an equation as true or false. If an equation were true, the correct response was a “Yes”. If an equation were false, the correct response was a “No”.

Once a response had been made, a feedback frame relating to the correctness of the subject’s response replaced the equation on screen (see Figure 4.3). Positive feedback (“RIGHT”) was displayed if an equation had been correctly identified (ie. subject responded “Yes” for a true equation or “No” for a false equation). Negative feedback (“WRONG”) was displayed if an equation had been incorrectly identified.
(ie. subject responded “Yes” for a false equation or “No” for a true equation). The feedback frame remained on screen for 400ms, and was then replaced by the next equation (see Figure 4.3).

Figure 4.3 Alphabet arithmetic stimulus and feedback presentation. Each equation was presented and remained on screen until a response was made by the subject. In order to maximise the number of equations subjects could process within the time-limited blocks, no inter-stimulus interval (blank) was inserted between feedback and the next equation.
4.2.2 Electroencephalographic recording

A helmet, designed and constructed at the Brain Sciences Institute, was used for the purpose of EEG recording (Ciorcari, Silberstein, Simpson & Schier, 1987). The helmet contained 64 silver-silver chloride electrodes which were lowered onto the scalp from a raised position in the helmet. Consistent contact between the scalp and electrode was maintained by the use of a conductive gel that was injected through the hollow centre of the tubular electrodes. The 64 electrodes utilized all of the electrode positions defined by the International 10-20 system, as well as additional sites located between those positions (see Figure 4.4). There was an average inter-electrode separation of 3.2cm (Silberstein et al., 1990).

Figure 4.4 Position of all 64 electrodes in helmet. This is a view from above the head, with the nose at the top and ears at the side. Black squares indicate International 10-20 System positions. Crosses indicate the 44 additional sites. The Rolandic and Sylvian sulci are marked by the transverse and lateral curved lines respectively.
The stimulus used to evoke the SSVEP consisted of a 13Hz sinusoidal flicker subtending a vertical angle of $90^\circ$ and a horizontal angle of $160^\circ$. The modulation depth of the stimuli when viewed against the monitor background was 45%. A set of half-silvered goggles which sat in front of the subject’s eyes allowed the sinusoidal flicker to be superimposed upon the subject’s viewing field and hence, the Alphabet Arithmetic stimuli (Figure 4.5). These goggles were attached to the front of the EEG helmet and lowered into position in front of the subject’s eyes prior to recording.

![Figure 4.5 Superimposition of SSVEP eliciting flicker on visual field. The half-silvered goggles reflected the flicker stimulus into the eyes of the subject, but simultaneously allowed the subject to view the task on the computer monitor. Two arrays of light emitting diodes (LED's) were the source of the 13Hz visual flicker, and because they were red in colour, gave a red tinge to the subject's visual field.](image-url)
Linked reference electrodes were attached to the earlobes and the nose served as the ground for all recordings. Brain electrical activity was amplified and bandpass filtered (3dB down at 0.1Hz and 30Hz) and then digitized to 12-bit accuracy at a rate of 200Hz (Silberstein et al., 1990; Silberstein et al., 1995a).

Figure 4.6 Experimental setup. After amplification and filtering, EEG data was written to the hard drive of the data acquisition computer for later off-line analysis, whilst response information (choice (Y/N), and timing information relating to the response) were recorded from the button box and written to the hard drive of the task computer.
4.3 Data analysis

4.3.1 Response time analysis

The problems of fatigue during performance of the task were evident from reports made by the subjects, most of whom found that the task was very demanding of their attention, and that they subsequently experienced lapses in concentration during which their performance would deteriorate. Such lapses could be expected to produce more incorrect responses and, perhaps more importantly, slower response times, which would have the effect of skewing the distribution of response times.

Another reason for skewing of the distribution is the physiological limit on response time, whereby most responses tend to be grouped around the lower end of the distribution with a number of extreme values at the high end. The data for this two-choice task typically showed this pattern of distribution, and as such, was slightly positively skewed. It is likely that high extreme values may have been the result of concentration losses reported by subjects.

Another type of extreme value (very short response times) may have been the result of responding based on habit, whereby a subject simply pressed a response button without considering the correctness of the equation (a number of subjects actually reported this type of responding - they got used to making “Yes” responses to a sequence of True equations, but did not change their response to a False equation that interrupted that sequence). As such, both these types of outliers almost certainly reflected processing that deviated from alphabet arithmetic calculation or memory-recall of the solution.

In order to try to eliminate these outliers, a process referred to as “Windsorizing” (p.110, Jensen, 1987) was carried out. For each subject, the response times to each of the four True equations were extracted from the overall response time data and then filtered by calculating the mean and standard deviation of the distribution, and discarding any individual response times lying outside two standard deviations from the mean. Although the criterion for outliers is any response time that falls outside of three standard deviations from the subject’s own mean response time (Jensen, 1987), it was felt that two standard deviations would be more effective in eliminating outliers that could possibly be associated with aberrant processing (eg. neither alphabet arithmetic nor memory-recall). This process had the effect of transforming the data to a close approximation of the normal distribution, such that
the mean could be used as a reliable and representative measure of the central tendency of the distribution of response times for each subject (Jensen, 1987).

4.3.2 Statistical analysis

Statistical analysis of response time data consisted of repeated measures ANOVA’s (Norusis, 1993a; 1993b), which were used to examine differences in task performance across the five Automatization blocks, as practice and learning occurred. Response time data and accuracy of responses for the four True equations across all five Automatization blocks were analyzed in separate $5 \times 4 \times 2$ (Block $\times$ Equation $\times$ Handedness) repeated measures ANOVA’s. For both of these ANOVA’s, Handedness was included as a between-subjects measure, since only responses to True equations (which required a right thumb-press) were evaluated, and handedness may have affected response time and accuracy. An analysis of the performance of the ten best subjects and the ten worst subjects was carried out in a further $5 \times 4 \times 2$ (Block $\times$ Equation $\times$ Group) repeated measures ANOVA, with Group (Best vs. Worst) as the between-subjects factor.

Curve-fitting of the response time data was obtained by non-linear regression, using the Marquardt-Levenberg algorithm, which chooses parameters that minimize the residual sum of squares difference between the observed and predicted values (Norusis, 1993b). This was used to assess whether the reduction in response time with practice followed a power law, a relationship observed in previous studies of practice, learning, and automatization.

4.3.3 Extraction of amplitude and latency components of the SSVEP

The electrophysiological response to the sinusoidal steady-state visual flicker stimulus was smoothed using a “running average” procedure. An epoch of a given length was selected to serve as an integration or ‘averaging window’, from which the amplitude and latency responses of the SSVEP were determined from its 13Hz Fourier cosine and sine coefficients. In this study, the epoch length chosen was ten cycles of the stimulus waveform. The ten cycle averaging period was then shifted one stimulus cycle along and the coefficients were recalculated for this overlapping
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4.3.4 Normalization

Large differences in SSVEP amplitude were evident between individual subjects, and in order to prevent skewing of pooled group data by subjects with extreme SSVEP amplitudes, it was necessary to “normalize” each subject's data prior to group averaging. This was achieved by selecting a task to act as a reference - in this case, the last Automatization block (A5) - and calculating the average SSVEP amplitude across that task for each electrode. The mean of these sixty-four values (one value for each electrode) was then calculated and all data at all electrodes was divided by this mean figure, giving a value close to one (1) for all subjects. This had the effect of minimizing between-subjects differences whilst retaining relative differences in the SSVEP within each subject.

4.3.5 Artifact detection

The SSPT has the advantage of being relatively insensitive to noise and muscular and ocular artifacts because such artifacts have their power spread over a wide range of frequencies whilst the power of the stimulus frequency is focused at 13Hz or its harmonics (Silberstein et al, 1990). Nevertheless, an artifact detection procedure was used to identify electrodes which showed excessive 'clipping' (activity...
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exceeding the dynamic range of the amplifier), or whose mean amplitude and latency data deviated significantly from those of its four nearest neighbours. Such electrodes were excluded from further analysis and their data replaced by a weighted mean of the data recorded from acceptable adjacent electrodes, which due to the relatively close spacing of the 64-channel system were expected to be highly correlated with their neighbours (Nunez, 1981).

4.3.6 Averaging of task events

Each trial within the six blocks consisted of a number of common events whose times of occurrence were logged by the computer on which the task was displayed. These events were; a) the presentation of the equation, b) a response to that equation and c) the presentation of feedback relating to that response. This allowed for each individual trial to be later identified in terms of which equation was presented, how long the subject took to respond to that equation, and whether the response made by the subject was correct or incorrect. During analysis, these parameters were used to select epochs of SSVEP data associated with specific events - for example, the SSVEP data associated with the presentation of True equations that were correctly responded to, whilst excluding epochs of SSVEP data associated with events that were not of interest (e.g., equations that were responded to incorrectly).

Selected epochs of data were centred about two events of interest that occurred during performance of each trial in the task. The first event was the time of presentation of each stimulus, which was chosen so that the activity immediately following presentation and relating to processing of the Alphabet Arithmetic stimuli could be investigated. The length of epoch was chosen to be 10 seconds because this allowed for observation of changes in the SSVEP for 5 seconds before and 5 seconds after presentation of the equation. This was necessary since the time taken to process equations during the Algorithmic block was relatively long, as indicated by the mean response time to those equations (2821ms - see Table 5.1, Results section).

The second event of interest about which the SSVEP data was averaged was the time of response to each Alphabet Arithmetic equation. This was done in order to allow observation of SSVEP changes associated with response selection and the period of feedback (evident as the 400ms of activity occurring immediately after the
time of response). To maintain consistency, the epoch length utilized for response averaging was also 10 seconds.

For this study, only the SSVEP data associated with verification of True Alphabet Arithmetic equations was considered, because there were half as many True equations as False equations to be learned, and each True equation was presented twice as often as each False equation. Since automatization is dependent upon the number of times each individual fact is presented (Logan & Klapp, 1991), the degree of learning for the True equations could be expected to be superior to the False equations. In other words, in the short period of time in which learning took place, the responses to the True equations could be expected to be faster and more accurate, more “automatic”, than responses to False equations. Therefore, concentrating the analysis on the responses to the True equations offered the possibility of observing optimum automatic performance of Alphabet Arithmetic.

For each subject, the epoch of data centred on the presentation (and response) of each True equation was extracted and pooled with other such epochs, and then averaged. This process was repeated for each electrode. Once a mean amplitude and latency value for each electrode within each subject had been calculated, the data for all 24 subjects was pooled and averaged again to give a cross-subject average of the SSVEP amplitude and latency associated with True verification performance. Two other groupings of pooled data were also made - the ten best performers and ten worst performers.

4.4 Topographic mapping

4.4.1 Amplitude and latency mapping

Topographic maps were produced from the time-series data, which displayed the amplitude and latency responses to the 13-Hz visual flicker at each electrode. This topographic mapping was done using an interpolation method based on spherical splines to estimate the amplitude and latency responses for areas of scalp between the electrode sites. This technique assumes a multi-layered, concentric sphere model of the head to represent conduction in the skull and scalp (Cadusch, Breckon & Silberstein, 1992).
To investigate changes in brain activity occurring with practice, it was necessary to be able to compare the brain activity at the beginning of the Alphabet Arithmetic task to brain activity after extended practice. There was no separate baseline task that could act as a reference from which comparisons about both the algorithmic task (block AL) and the automatized task (block A5) could be drawn. Therefore, one of the task blocks was chosen to act as the reference for all of the tasks, including itself. For this study, the last Automatization block (A5) was chosen to act as the baseline for all other tasks in order to document the changes in SSVEP responses occurring with practice and learning from block AL to A5. As such, all interpretations of amplitude and latency changes are relative to the mean levels of amplitude and latency (respectively) of this task.

In order to show the differences in SSVEP response between tasks, the SSVEP amplitude and latency data for a given task needed to be compared to the reference task, which was done by subtracting the amplitude and latency responses of a given task from the mean amplitude and latency values of the reference task (A5). In subtracting the SSVEP responses from one another, difference maps were created which subtracted out common, non-specific effects such as those due to general attentional demands, whilst retaining the differences in amplitude and latency between the given task and the mean level of the reference task (A5). Therefore, all difference topographic maps allow comparison of the tasks to each other through mutual comparison with a common reference task.

4.4.2 Statistical probability maps

These topographic maps indicate how significant the combined differences in SSVEP amplitude and latency responses were between two tasks. They were based on the Hotelling’s $T^2$ parameter and the results were illustrated by using significance probability mapping (Duffy, Bartels & Burchfield, 1981) to show the scalp topography of the statistical strength of these differences.

The Hotelling’s $T^2$ measures were based on multiple bivariate t-tests of the difference between the mean levels of amplitude and latency in the baseline task (A5) and the amplitude and latency time series data of the task of interest. P-values indicating the significance of these differences corresponded to given t-values, which were obtained by taking the positive square-root of the $T^2$ value, using one degree of
freedom for the numerator and n-1 (where n = the number of subjects) degrees of freedom for the denominator. For the data averages across all subjects (n = 24), these t-values were 2.81 and 3.77, and corresponded to significance levels of 1% and 0.1% respectively. For the averages of the Best and Worst performers, where each group contained ten subjects, the t-values were 3.25 and 4.78, and corresponded to significance levels of 1% and 0.1% respectively.

The Bonferroni correction was used to account for the fact that multiple independent comparisons of the SSVEP data were made. Strict application of this criterion would take into account all 64 electrode sites, but this incorrectly overlooks the fact that the electrodes will be highly correlated with each other. Spatial principal components analysis suggests that a smaller number that takes into account the correlation between electrodes better reflects the dimensionality of the topographic data. Five factors have been found to be capable of accounting for 95% of the variance of such data (Duffy, Jones, Bartels, Albert, McAnulty & Als, 1990; Silberstein & Cadusch, 1992), and so for a single comparison of SSVEP data based on 64 electrodes, the adjusted p-value would be 0.05/5 or 0.01 (1%). However, if each Hotelling’s map is considered to be an independent comparison, then a further adjustment to the p-value would be 1% divided by the number of Hotelling’s maps (8; 4 for each session, AL & A5) = 0.125%. The Hotelling’s statistical probability maps show contours corresponding to p-values of 0.1%, which approximates the Bonferroni corrected p-value of 0.125% (Silberstein et al., 1995a). Therefore, the null hypothesis (that there will be no difference in SSVEP amplitude or latency between the task of interest and the reference task, A5) can be rejected if p<0.1% for any of the maps.

4.5 Conclusion

This study was designed to create conditions whereby unpracticed and therefore slow, non-automatic processing could be compared with practiced, automatic processing. Accordingly, the alphabet arithmetic task was designed to promote non-automatic, counting processes during the Algorithmic block by using a large number of equations, whilst the remaining blocks were designed to promote the development of automatic performance (via memory-retrieval) within a short period of time by using a small number of equations.
Even with this smaller number of equations, the greater number of presentations of True alphabet arithmetic equations led to an enhanced likelihood of observing automatic processing for such equations, and so analysis of both response times and the SSVEP response was confined to data relating only to performance of True equations.

Given that this study utilised a subtraction methodology to investigate the electrophysiological changes with practice, the SSVEP data should be interpreted in terms of a relationship with the reference task (the mean amplitude or latency of the Automatization block, A5). That is, the SSVEP amplitude and latency for any given task (e.g., the Algorithmic block, AL) will show an increase or decrease relative to the reference task. Statistically, differences between a given task and the reference will be significant for a p-value less than the 0.1% level.
Chapter 5

Results

The Method chapter outlined the structure of the Alphabet Arithmetic task and how it was presented to subjects, as well as how both the response time and SSVEP data was recorded and analysed. The aim of this chapter is to present that data, and to highlight the main findings of this study, in terms of the nature of the performance of the subjects (i.e., non-automatic vs. automatic processing), and the associated SSVEP responses.

Firstly, the behavioural (response time) data for all subjects will be presented with a view to evaluating task performance during the Algorithmic and Automatization blocks (Section 5.1). Following this, Section 5.2 will compare the results for two sub-groups of the pooled data (Best and Worst performers) in terms of automaticity of performance during the Automatization block (A5). Section 5.3 will present the pooled SSVEP data for the two main stages of task performance that represent effortful, controlled processing, and automatic processing respectively - the Algorithmic block (AL) and the Automatization block (A5). Given the performance differences between groups of individuals which became evident from the response time data, a comparison of SSVEP responses for the Best and Worst performers will also be made.

5.1 Behavioural data for all subjects

5.1.1 Response time and accuracy data

There was a decrease in the average response time to True equations across the five automatization blocks, and there was a large difference in response time between the algorithmic block (AL) and the first automatization block (A1), although the standard deviations were reasonably similar (Figure 5.1a; see also Table 5.1).
A preliminary t-test of the mean response times revealed that there was a significant difference in response time between the Algorithmic block (AL) and the Automatization block (A5) \((t(23,1) = 10.25, p<.05)\). This was expected since the Algorithmic block was designed to promote slow response times whilst the Automatization block (A5) was expected to show fast response times.

The length of each task block was identical and, as can be seen from Figure 5.1, the number of trials that subjects were able to perform in the same period of time increased substantially with practice. By the last Automatization block, subjects were averaging more than three times as many trials than they were in the Algorithmic block, and had increased the number of trials performed across A1-A5 by 70% (see Appendix A, Table A.1).

A repeated measures ANOVA was used to look at the response time data for the Automatization blocks (A1-A5). Overall, there was a significant difference in response time between the Automatization blocks \((F(4,19)=19.10, p<.01)\). Univariate results from the Block × Equation × Handedness ANOVA showed where the differences between the Automatization blocks lay. There was a significant difference between the first two blocks combined and the third, fourth and fifth blocks combined \((F(1,22)=83.85, p<.01)\); and between the middle three blocks (A2, A3 & A4) combined, and the first and last blocks combined \((F(1,22)=37.99, p<.01)\).

<table>
<thead>
<tr>
<th>Block</th>
<th>Mean Response Time</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithmic (AL)</td>
<td>2821ms</td>
<td>1000ms</td>
</tr>
<tr>
<td>Automatization 1</td>
<td>1869ms</td>
<td>900ms</td>
</tr>
<tr>
<td>Automatization 2</td>
<td>1442ms</td>
<td>665ms</td>
</tr>
<tr>
<td>Automatization 3</td>
<td>1179ms</td>
<td>503ms</td>
</tr>
<tr>
<td>Automatization 4</td>
<td>1083ms</td>
<td>497ms</td>
</tr>
<tr>
<td>Automatization 5</td>
<td>1006ms</td>
<td>471ms</td>
</tr>
</tbody>
</table>
Figure 5.1 Mean response time (A) and mean accuracy (B) for each task block. Response time decreased with practice (across the task blocks), and there was a corresponding increase in number of trials performed per block. Accuracy improved with practice, but the increase was not significant.

Both left- and right-handed subjects were used in this study, but only responses to True equations (which required a button-press with the right thumb) were analysed. Therefore it was necessary to determine whether handedness may have influenced response times to the equations. Handedness was treated as a between-
Subjects factor in the $5 \times 4 \times 2$ (Block $\times$ Equation $\times$ Handedness) ANOVA, but there was no overall effect of handedness on response time across the five Automatization blocks ($F(22,1)=0.01, p>.01$).

Accuracy of response was relatively high, averaging just under 93% across the five Automatization blocks (see Figure 5.1b). Mean accuracy was lowest for the Algorithmic block (86%) but increased rapidly between the first and second Automatization blocks, peaking by the last Automatization block (Figure 5.1b, also Table A.2). However, although the increase in mean accuracy of responses across the entire task (including the Algorithmic block) was significant ($F(18,5)=5.64, p<.01$), the improvement across the five Automatization blocks only was not significant ($F(19,4)=2.51, p<.01$).

T-tests between individual blocks revealed that there were significant differences in accuracy between AL and A5 ($t(23,1)=-3.95, p<.05$, 2-tailed), and between A1 & A2 ($t(23,1)=-2.91, p<.05$). There was no difference in mean accuracy between AL and A1 ($t(23,1)=-0.68, p>.05$).

The effect of handedness on response accuracy was assessed because only the data from responses to True equations was examined. Since True equations required a “Yes” response using the thumb of the right hand, there was a possibility that handedness may have affected how accurately subjects responded to the True equations, and this was investigated using a $5 \times 2$ (Block $\times$ Handed) ANOVA. However, there was no significant difference in overall accuracy between right and left handed subjects ($F(22,1)=2.77, p>.01$) across all five Automatization blocks, nor across the entire task, including the Algorithmic block ($F(22,1)=1.54, p>.01$, $6 \times 2$ ANOVA).

5.1.4 Response time data for individual equations

Mean response times to each individual True equation for all five Automatization blocks are displayed in Figure 5.2. There were significant overall differences in response time between the four True equations ($F(3,20)=8.59, p<.01$), but there was no significant difference in response time between equations with +3 and +4 addends ($F(3,20)=0.65, p>.01$).
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Figure 5.2 Decrease in mean response time with practice for each True equation. A consistent response time relationship between the four equations was evident across all five blocks.

However, there was a significant difference in response time between T+3=W/H+4=L combined and T+4=X/H+3=K combined (F(3,20)=24.19, p<.01) which can be seen from the response time separation of T+3=W and H+4=L from T+4=X and H+3=K in Figure 5.2.

There was no effect of Block on Equation in the Block × Equation interaction (F(12,11)=1.84, p>.01). That is, there was no change in the relationship between the equations across the blocks as learning occurred. In Figure 5.2, this is reflected in the consistent graded response times to each True equation; responses to H+4=L were consistently slowest, T+3=W responses were slightly faster, H+3=K responses were slightly faster again and responses to T+4=X were consistently the fastest across all five Automatization blocks.
5.1.5 Differences between equation types

The graph in Figure 5.3a shows the difference in response times within each block between True equations with addends of three and addends of four. In the Algorithmic block, in which subjects needed to use a counting algorithm to perform alphabet arithmetic, +3 equations were responded to significantly faster on average than the +4 equations ($t(23,1)=6.24$, $p<.05$). This difference decreased to a non-significant level (20ms) for the first Automatization block, and remained non-significant for all five Automatization blocks ($F(23,1)=0.19$, $p>.05$; see also Appendix A, Table A.3).

Mean response times for T-based equations were consistently faster than for H-based equations for all Automatization blocks (see Figure 5.3b), although the differences overall were once again small and non-significant ($F(3,20)=2.50$, $p>.01$) (see Table A.4).

The results relating to the effects of addend and equation base (letter) suggest that no particular type of equation (+3\,+4, H\,T) was responded to faster than any other type. Rather, it shows that there was a consistent relationship between each individual equation and response time, although response times between individual equations were not significantly different. It was expected that response times to +4 equations would be slower initially, and perhaps that T-based equations would be responded to more slowly because of reduced familiarity with the last half of the alphabet, but that these differences would diminish as retrieval processes became more dominant. However, it seems that particular equations were consistently responded to faster from the beginning of practice (i.e., H+3=K, T+4=X).
Figure 5.3 Response time differences between equation types. Only during the Algorithmic block were the response time differences between +3 and +4 equations significant (A). Overall, mean response times for T-based equations (T+3=W; T+4=X) were slightly faster than for the H-based equations (H+3=K; H+4=L) in all automatization blocks (B), although these differences were not significant.
5.1.6 Power law decrease in response time with practice

The observed reduction in response time with practice followed a power law, consistent with previous studies of extended practice, learning, and theories of skill acquisition (Logan, 1988a; Newell & Rosenbloom, 1981; Crossman, 1959; Fitts, 1964). This result is illustrated by the plot of the response time data as a function of number of presentations and the corresponding power law fit of the data shown in Figure 5.4a. The fit of the response time data was obtained by non-linear regression, and yielded an $R^2$ value of 0.89, which can "be interpreted as the proportion of the total variation of the dependent variable around its mean that can be explained by the fitted model" (Norusis, 1993b, p.220). As such, it would appear that the response time data is reasonably well fit by the power law model.

![Power Law Fit of Response Time](image)

Figure 5.4A  Power law fit of response time as a function of number of trials. For each trial, the corresponding response time value is the mean of response times for that trial across all 24 subjects.
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Figure 5.4B Log-log plot of mean response time as a function of number of trials. All subjects (n=24) correctly performed at least 64 trials of each of the four True equations, but only 13 performed more than 100 presentations of each equation. The deviation in the tail of the graph is due to a convergence of mean response time on the response times of the faster subjects who performed more trials.

Given the power law decrease with practice, plotting the Alphabet Arithmetic data on log-log coordinates yielded a comparatively straight line, also consistent with previous research on learning (Newell & Rosenbloom, 1981). However, it also revealed a discontinuity in the response time-number of presentations relationship, which began after about the 70th presentation. This anomaly was due to the fact that there was a decreasing number of subjects who managed to perform a large number of presentations (see Figure 5.4b). Hence, as the number of presentations increased, the average response time began to converge on the response times of the faster subjects, who were able to perform a large number of presentations.
5.2 Behavioural data for Best and Worst performers

5.2.1 Response time and accuracy data

Although the pooled response time data showed a power law reduction with practice consistent with previous studies of learning and automaticity (Newell & Rosenbloom, 1981; Logan, 1988a), and a mean response time in the last Automatization block (A5) suggestive of automatic processing (1006ms), closer inspection revealed that by the end of practice, some subjects were still responding extremely slowly to the Alphabet Arithmetic stimuli.

Since the purpose of this study was to investigate the possible differences in electrophysiology between non-automatic and automatic processing, it was important to establish that performance during the last Automatization block (A5) was indeed automatic.

The predominant measure of automaticity has been response time (Crossman, 1959; Newell & Rosenbloom, 1981) and in order to maximise the possibility of observing automatic processing, it was necessary to separate subjects displaying performance indicative of automatic processing from those who subjects who did not. Subjects with response times under one second by the end of practice formed the Best performers group, and the response time and SSVEP data was analysed separately from the Worst performers group, which consisted of the ten subjects with the slowest end of practice response times. The superior performance of the Best group was reflected in faster mean response times at all stages of task performance and generally greater accuracy (see Figures 5.5a & 5.5b), although the overall difference in accuracy between the groups was not significant.

Table 5.2

Mean Response Times and Standard Deviations for Best and Worst Performers

<table>
<thead>
<tr>
<th>Block</th>
<th>Best RT</th>
<th>Std. Dev.</th>
<th>Worst RT</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithmic (AL)</td>
<td>2434ms</td>
<td>710ms</td>
<td>2920ms</td>
<td>876ms</td>
</tr>
<tr>
<td>Automatization 1</td>
<td>1471ms</td>
<td>708ms</td>
<td>2159ms</td>
<td>868ms</td>
</tr>
<tr>
<td>Automatization 2</td>
<td>1132ms</td>
<td>416ms</td>
<td>1745ms</td>
<td>699ms</td>
</tr>
<tr>
<td>Automatization 3</td>
<td>921ms</td>
<td>247ms</td>
<td>1512ms</td>
<td>563ms</td>
</tr>
<tr>
<td>Automatization 4</td>
<td>821ms</td>
<td>196ms</td>
<td>1399ms</td>
<td>580ms</td>
</tr>
<tr>
<td>Automatization 5</td>
<td>765ms</td>
<td>179ms</td>
<td>1329ms</td>
<td>574ms</td>
</tr>
</tbody>
</table>
Figure 5.5 Mean response time (A) and mean accuracy (B) for each block for Best and Worst performers. Best performers were consistently faster and more accurate than Worst performers across the Automatization blocks, but only the overall response time difference was significant.
The overall difference in mean response times between the Best and Worst performers is apparent in Figure 5.5a. Although the difference between mean response times during the Algorithmic block was not significant ($t(18,2)=0.60, p>.05$, 2 tailed), there was a significant difference between the groups in mean response time within A5 ($t(18,2)=4.88, p<.05$, 2 tailed) and overall across the five Automatization blocks ($F(18,1)=39.12, p<.05$).

T-tests of differences in response times showed that there were significant differences between AL and A5 within both groups ($t(9,1)=6.49, p<.05$ (Best), $t(9,1)=5.88, p<.05$ (Worst)), indicating that performance during block A5 was significantly faster than performance during block AL for both groups.

Comparisons of accuracy between the Best performers and Worst performers revealed that there was no difference in the mean accuracy of responses between the two groups ($F(18,1)=0.27, p>.01$, 6 × 2 ANOVA) for the entire task including the Algorithmic block, nor for the Automatization blocks only ($F(18,1)=0.26, p>.01$, 5 × 2 ANOVA).

Separate 6 × 2 Repeated measures ANOVA for each group revealed no significant increase in response accuracy across the blocks within either group; $F(5,5)=4.14144, p>.01$ (Best) and $F(5,5)=2.06063, p>.01$ (Worst). There was no significant difference in mean accuracy between AL and A1 for either group (Best, $t(9,1)=1.62, p>.05$; Worst, $t(9,1)= -1.09, p>.05$), nor between A1 and A2 (Best, $t(9,1)= -3.19, p>.05$; Worst, $t(9,1)= -0.97, p>.05$).

### 5.2.2 Response time data for individual equations

Figure 5.6 shows the difference in mean response time between each True equation within both the Best and the Worst performance groups, and also makes evident the overall difference in mean response times between the two groups.

There was no effect of block on group ($F(3,16)=0.48, p>.01$); that is, the response time relationship between the two groups was consistent across the five Automatization blocks. The Group × Equation interaction showed that there was no significant difference in the relationship between the equations between the Best and Worst performers; that is, the graded response to the individual equations (H+4, T+3, H+3, T+4 in order of decreasing response time) was similar in both groups ($F(3,16)=0.57, p>.01$).

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From Figure 5.6 it can be seen that there was a greater spread of response times between the four True equations for the Worst group, whereas the Best group showed less variation between equations. However, separate MANOVA’s for each group revealed that within each group there was no significant difference in response times between the four True equations $F(3,7)=1.92$, $p>.01$ (Best) and $F(3,7)=5.76$, $p>.01$ (Worst).

Although both groups showed significant differences in response time between +3 and +4 equations during the Algorithmic block ($t(1,9)=3.38$, $p<0.05$ (Worst), $t(1,9)=4.11$, $p<0.05$ (Best)), there were no significant differences across blocks A1-A5 ($F(1,9)=0.122$, $p>0.01$ (Worst), $F(1,9)=0.945$, $p>0.01$ (Best)).
5.2.3 Power law reduction in response time with practice

Best performers were faster at the beginning of the Automatization blocks (early trials) and consistently faster at all stages of practice. Both Best and Worst performers exhibited a power law reduction in response time with practice (Figure 5.7), but the 'asymptote' of performance (mean response time for last trial performed) was lower for the Best performers, such that their performance at the end of practice was fast enough to be considered automatic.

![Power Law Fit of Response Time](image)

Figure 5.7 Power law decrease in response time with practice for Best and Worst performers. Each response time value is an average across the ten subjects in each particular group.

Despite the fact that the Worst performers' responses were slower overall and they did not appear to automatize, the similar rate of reduction in response time with practice to the Best performers was evident in the similarity of the exponents for the power law fits between the two groups (0.213, Worst vs 0.248, Best). Clearly, the response time data for the Best performers ($R^2=0.93$) was fit better by the power law model than the Worst performers ($R^2=0.81$). The poorer fit of the Worst performers data was due to the greater variability in response time (evident in greater standard deviations - see Fig. 5.5A, Table 5.2) compared to the Best performers.
5.3 Electrophysiological Results

5.3.1 Time-series Data

The time-series data shows four seconds of SSVEP amplitude and latency data as waveforms, averaged for True equations across all 24 subjects, and centred on the time of presentation of the alphabet arithmetic equations.

Figures 5.8A & 5.8B illustrate SSVEP amplitude at a frontal midline and left occipital electrode site. Whilst processing of the equation was associated with a transient decrease in amplitude occipitally in both the algorithmic and automatization blocks (Figure 5.8B), practice appears to have produced little difference in that amplitude. However, a large sustained difference between the blocks was evident frontally, indicating that amplitude decreased with practice (Figure 5.8A). Dynamic or transient changes in amplitude associated with task performance were also evident frontally, with processing being associated with a transient increase in amplitude in the algorithmic block, and a transient decrease in amplitude in the automatization block (Figure 5.8A).

Figure 5.8 SSVEP Amplitude and Latency at Electrodes 8 (Frontal Midline) and 59 (Left Occipital)
Figures 5.8C & D also show cross-subject averages (n=24) of SSVEP latency at the same electrode sites. Sustained latency differences between the algorithmic and automatization blocks were evident left occipitally (Figure 5.8D), with latency increasing with practice (the automatization block had a longer latency than the algorithmic block). On the other hand, sustained latency differences were not evident frontally, but dynamic, task-related changes in latency were evident (Figure 5.8C). In the algorithmic block, processing of the equations was associated with a transient decrease in latency whilst during the automatization block, processing was associated with an increase in latency.

Overall, it appears that dynamic or transient task-related changes in amplitude and latency were more evident in frontal regions. Practice appeared to produce transient reductions in amplitude and transient increases in latency in frontal regions during processing of the alphabet arithmetic equations, as well as a sustained, practice-related reduction in amplitude most prominent frontally, and a practice-related increase in latency occipitally.

### 5.3.2 Transient Changes in the SSVEP Response during Task Performance

The transient changes in SSVEP amplitude and latency during task performance suggested by the time-series data (Figure 5.8) are perhaps best illustrated topographically (Figures 5.9 & 5.10). Maps of SSVEP amplitude and latency for the entire scalp were derived by interpolation from the time-series data at each electrode, and are a view from above the head (with the nose at the top and ears at the side), with the Rolandic and Sylvian sulci marked by the transverse and lateral curved lines respectively.

These maps illustrate differences in amplitude and latency between the algorithmic block and the reference task (mean amplitude and latency of the automatization block) (Figure 5.9), and differences in amplitude and latency between the automatization block and the reference task (mean amplitude and latency of the automatization block) (Figure 5.10). They illustrate SSVEP amplitude and latency data averaged across both subjects and trials during four main aspects of task performance: presentation of the equation, processing of the equation, response and feedback.
Figure 5.9: Topographic illustration of time series data for all subjects during Algorithmic block (AL). Regions where SSVEP amplitude or latency was increased relative to the reference task are indicated by cooler colours (blue), and regions where amplitude or latency was decreased relative to the reference task are shown as warmer colours (orange/pink). The third row of statistical parametric maps illustrate the significance of the combined amplitude and latency differences between each block and the reference block (A5).
Figure 5.10 Topographic illustration of time series data for all subjects during Automatization block (A5).
5.3.3 Mean SSVEP Levels within each Task

The mean level topographic maps (Figure 5.11) display the average value of the amplitude and latency across an entire block for all subjects (n=24). To obtain this average, all of the SSVEP values for each electrode during each block were collapsed into a single (mean) value, giving an indication of the average SSVEP response at that electrode for that block as a whole. The maps show the difference between mean SSVEP amplitude & latency in each task and the mean amplitude and latency in the Automatization block (A5).

Unlike the previous high temporal resolution maps, which show SSVEP activity during the four main stages of task performance, these maps are an average of the activity across those four stages. The first two columns illustrate the mean SSVEP amplitude and latency for each task block compared to the mean amplitude and latency of the reference task (block A5). Just as for the previous high temporal resolution maps, cooler colours indicate regions where the SSVEP amplitude or latency is higher than the reference task, and warmer colours indicate regions where the amplitude or latency is lower than the reference task. The third column of statistical parametric maps illustrates the significance of the combined amplitude and latency differences between each block and the reference block (A5).

These maps give a rough indication of the changes in amplitude and latency associated with practice across the six task blocks, and clearly show the decrease in amplitude and increase in latency (particularly in frontal regions) associated with practice.
Figure 5.11 Cross-subject average (n=24) of mean SSVEP amplitude and latency for each block.
However, as already suggested by the response time data, it was evident that a number of subjects showed superior performance on the Alphabet Arithmetic task, and that some subjects did not appear to automatize their responses, even by the fifth automatization block (A5). Therefore, it seemed possible that just as the pooled response time data suggested that all subjects automatized (but actually masked differences between good performers and poor performers), the pooled SSVEP data may have masked differences in SSVEP response between the groups.

This possibility was initially investigated by obtaining the mean values of the SSVEP data during each block for each group separately (Best & Worst performers). Whilst both groups showed increased amplitude and decreased latency during performance of the Algorithmic task, Worst performers showed increased amplitude and decreased latency consistently during each practice block (Figure 5.12). On the other hand, Best performers showed a decrease in amplitude and an increase in latency which developed across the blocks (Figure 5.13).

The different topographies for the Best and Worst performers during the Automatization block (A5) supported the suggestion that the differences in response time between the two groups might be associated with differences in SSVEP response between the two groups.

Given that the response time data suggested that the Worst performers did not automatize, and that both groups showed different response times and mean level SSVEP data, further investigation using high temporal resolution topographic mapping was carried out to determine whether these differences in SSVEP response between the groups occurred during the processing stage of task performance.
Figure 5.12 Cross-subject average (n=10) of Worst performers mean SSVEP amplitude and latency for each block.
Figure 5.13 Cross-subject average (n=10) of Best performers mean SSVEP amplitude and latency for each block.
5.3.4 Transient Changes in the SSVEP Response during Task Performance for Best and Worst Performers

Since the mean level topographic maps averaged the SSVEP response across the entire task, the transient changes in SSVEP amplitude and latency associated with the different stages of task performance during each trial were not visible. Therefore, it was desirable to use a higher resolution (~380msecs) to reveal such changes. As with the previous high-resolution topographic maps for the pooled data, these maps are averages across subjects and trials during four main aspects of task performance; presentation of the equation, processing of the equation, response and feedback.

5.3.4.1 Processing during the Algorithmic block (AL)

Both groups showed a frontal and central amplitude increase relative to the mean level of A5 that was sustained during task performance. Also, both groups showed an occipital amplitude decrease that began at presentation of the Alphabet Arithmetic equation, but whilst the decrease occurred bilaterally for the Best Performers (Figure 5.14) it was smaller and confined to the right occipital region for the Worst Performers (Figure 5.15). For both groups, this amplitude decrease was maximal during processing of the equation, but was diminished at presentation, response and during feedback. The Worst Performers also showed a small, transient amplitude decrease pre-frontally during response and feedback, whereas no such change was evident for the Best Performers.

For both groups, performance during the algorithmic task was characterised by a sustained increase in amplitude frontally, and a transient latency decrease in frontal regions associated with processing of the equation.

The Best group showed significantly different amplitude and latency levels from the reference task in the left occipito-parietal region during processing of the Alphabet Arithmetic stimuli, whilst for the Worst performers, amplitude and latency differed most in the left occipital and pre-frontal regions during processing.
Figure 5.14 High temporal resolution topographic difference maps of SSVEP amplitude and latency for Best performers during Algorithmic block (AL), plus statistical parametric maps of combined latency and amplitude differences between the Algorithmic task and mean level of the Automatization task (A5).
Figure 5.15 High temporal resolution topographic difference maps of SSVEP amplitude and latency for Worst performers during Algorithmic block (AL), plus statistical parametric maps of combined latency and amplitude differences between the Algorithmic task and the mean level of the Automatization task (A5).
5.3.4.2 Processing during the Automatization block (A5)

For both the Best and Worst performers, performance during the Automatization block (A5) was associated with an overall decreased SSVEP amplitude compared to the Algorithmic block. For the ten Best subjects, processing of the equation was associated with a transient amplitude decrease and latency increase frontally (Figure 5.16). However, for the ten Worst performing subjects, the most prominent transient, task-related changes were a transient amplitude decrease occipitally and a latency decrease frontally and left parieto-temporally (Figure 5.17).

The statistical parametric maps reflect the differences between the mean level of amplitude and latency for the last block and the actual amplitude and latency at the various stages of task performance. Best performers showed significant differences in amplitude and latency responses in frontal and central regions, whilst the Worst performers showed differences in the right occipital region during processing of the Alphabet Arithmetic equations (see Figures 5.16 & 5.17).
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Figure 5.16 High temporal resolution topographic difference maps of SSVEP amplitude and latency, and statistical parametric maps for Best performers during the Automatization block (A5). Statistical parametric maps show differences between combined amplitude and latency in the Automatization task and the mean level of amplitude and latency in the Automatization task (A5).
Figure 5.17 High temporal resolution topographic difference maps of SSVEP amplitude and latency, and statistical parametric maps for Worst performers during the Automatization block (A5).
5.4 Conclusion

The response time data was used as a performance measure for the Alphabet Arithmetic task, and hence as a guide to the automaticity of performance achieved by individual subjects, and also as the criteria for the grouping of subjects. The response time data suggested that performance during the Algorithmic block was slow, effortful and non-automatic for all subjects, including the Best performers. Performance during this stage of the task was characterised by increased SSVEP amplitude and decreased latency in frontal regions for both Best and Worst performers.

For the Automatization block (A5), the response time data suggested that only the performance of the Best performers was at a level fast enough to be considered automatic. Automatic performance of the task (by the Best performers) was characterised by reduced SSVEP amplitude and increased latency in frontal regions, whilst even after extended practice, the Worst performers displayed response times indicative of non-automatic performance, characterised by increased SSVEP amplitude and decreased latency frontally, a pattern of activation similar to the Algorithmic block.
Chapter 6

Discussion

The results revealed that both the Best and Worst performers showed evidence of slow, non-automatic processing during the Algorithmic block, but whilst both groups showed a similar rate of reduction in response time with practice, only the Best performers automatized and showed a different SSVEP topography in the Automatization block. The purpose of this chapter is to relate these results to the concepts of non-automatic and automatic processing, and to tie these results in to previous findings in the literature.

A short overview of the results and their relation to the original hypothesis will be given in Section 6.1. Following this, the results for the Algorithmic block will be discussed, and the role of working memory in effortful, non-automatic processing will be reviewed, particularly in relation to number arithmetic, prior to a discussion of the possible association between working memory and SSVEP activity during the Algorithmic task (Section 6.2). SSVEP activity during the Automatization block will be discussed in terms of previous findings of reductions in brain activity after extended practice (Section 6.3), whilst a speculative discussion of the possible role of inhibitory mechanisms in automatic performance (Section 6.4) will conclude the body of the chapter.

6.1 Overview of electrophysiological results

Initial performance of Alphabet Arithmetic showed increased SSVEP amplitude and decreased latency consistent with the pattern previously observed during a working memory task (Silberstein, 1997), as well as increased amplitude and decreased latency in parietal regions (although this was not evident after extended practice - see Section 6.5.2). Conversely, well-practiced, automatic Alphabet Arithmetic (Best performers) showed decreased SSVEP amplitude and increased latency, a pattern opposite to the Algorithmic block and perhaps suggestive of a decrease in the 'rejection' component of the task or a decreasing dependence on working memory. As such, the hypothesis that automatization of Alphabet Arithmetic
would be associated with a decrease in SSVEP amplitude was supported, and the results were consistent with other findings (Haier et al., 1992, Raichle et al., 1994, Pauli et al., 1994; 1996) suggestive of a reduction in frontal brain activity with practice.

6.2 Algorithmic session (AL) - unpracticed performance

In the initial stages of performance (during the Algorithmic block), all subjects showed response times suggestive of controlled, effortful processing. That is, long response times, and a significant increase in response time associated with an increase in magnitude of the addend, suggestive of the utilization of counting processes (Groen & Parkman, 1972; Logan, 1988a; Ashcraft et al., 1992). Even the Best performers, whose response times at all stages of the task were significantly faster than the Worst performers, showed a mean response time of 2552ms and a significant difference in response time of 214ms between the +3 and +4 equations during the Algorithmic block (see Table A.5). Accordingly, the SSVEP data for all twenty-four subjects and both the Best and Worst performing groups during the Algorithmic block (AL) was considered to reflect non-automatic processing.

Both Best and Worst performers showed increased SSVEP amplitude and reduced SSVEP latency in frontal regions during the Algorithmic task which was inferred as an increase in brain activity. This is consistent with previous findings of higher levels of frontal brain activity for novel or unpracticed conditions (compared to practiced conditions) for tasks such as verb-generation (Petersen et al., 1989; Raichle et al., 1994), production of answers to arithmetic equations (Pauli et al., 1994; 1996) and perceptual-motor tasks such as the computer game Tetris (Haier et al., 1992).

Frontal activity has been suggested to reflect attentional involvement and the use of controlled, effortful processing (Casini & Macar, 1996; Stevens et al., 1997), the use of calculation procedures in mental arithmetic tasks (Pauli et al., 1994) and utilization of “an executive function which allocates resources and/or coordinates a number of the processing stages” (Ruchkin et al., 1988, p.485). Activation of frontal regions during the Algorithmic session is consistent with the suggestion that control processes are more likely to occur in the initial stages of training and during the performance of difficult tasks, and are more dependent upon frontal lobe function than automatic processes (Moscovitch & Winocur, 1992).
6.2.1 Controlled processing and working memory in arithmetic

The involvement of conscious, controlled processing in mental arithmetic is suggested by the existence of the problem-size effect, interactions with concurrent tasks, priming effects (Ashcraft et al., 1992; Koshmider & Ashcraft, 1991), and effects of intention (Zbrodoff & Logan, 1986).

Such attentional effects and utilization of control processes implicates a role for working memory, since the working memory approach to attention and automaticity views attention in a similar manner as the controlled processing (Shiffrin & Schneider, 1977) or conscious processing (Posner & Snyder, 1975) approaches (Ashcraft et al., 1992). Despite the unsatisfactory nature of the resource approach to the transition to automatic processing, it is suggested that the concept of attentionally-demanding, controlled processing has utility in explaining unpracticed, effortful performance (Cohen, Dunbar & McClelland, 1990). Consequently, working memory is viewed as a specific resource, within which exists an allocation of attention (Ashcraft et al., 1992, p302). As such, processes that require attention involve working memory and are viewed as conscious and effortful, whilst those that do not require attentional resources are viewed as automatic and are equated with elementary automatic component processes, such as obligatory activation and retrieval of knowledge from memory (Ashcraft et al., 1992).

For arithmetic calculation, it is generally agreed that there is a need for temporary storage of information (Logan, Gilhoolie & Wynn, 1994), and working memory is viewed as a “brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning and reasoning” (p.556, Baddeley, 1992).

Hitch (1978a) viewed working memory as a storage system for both initial operands and intermediate values computed during arithmetic performance. Hitch (1978a) used arithmetic problems involving 2, 3 or 4 digit numbers multiplied by a single digit number. Results showed an increase in errors in the tens column as the size of the multiplicand increased from 2 to 3 to 4 digits, suggesting that working memory was involved in the computation of answers for complex arithmetic problems. Hitch (1978b) also found increased errors when subjects were required to write answers in their reverse order, as the number of carry operations in a problem increased, and
when the storage time of initial or intermediate values increased, because this increased the demand on working memory.

Few studies investigating working memory and arithmetic specifically describe the nature of the memory system involved (Logan, Gilhoolie & Wynn, 1994). Some conceptualizations view working memory as a single, multifunctional system responsible for the storage and processing of information and the allocation of attention (i.e., Geary & Widaman, 1992), whilst others propose a multiple component system (i.e., Baddeley & Hitch, 1974). This multiple component system consists of a central executive plus two slave storage systems, such that the central executive is involved in coordinating the activity of the two slave systems and can operate on the information held in those buffers (Baddeley & Hitch, 1974; Baddeley, 1986; 1992).

Despite the differences in conception, the attributes of the single system roughly correspond to those of the central executive component of the Baddeley & Hitch (1974) model, and it is this component, whether realised as a part or the entirety of working memory, that is thought to be involved in calculation for arithmetic tasks (Logie, Gilhooly & Wynn, 1994). Logie, Gilhooly & Wynn (1994) suggested that performance of arithmetic tasks requires the central executive component to perform the calculations and produce approximately correct answers, and a sub-vocal rehearsal component to maintain accuracy (based on findings that suppression of articulation of arithmetic problems by a concurrent verbal task adversely affected performance).

Evidence for the involvement of the central executive in arithmetic comes from interference effects caused by a concurrent, secondary task, such as random generation of items from a well-known set (e.g., the alphabet or single-digits). Random generation has been shown to adversely affect card sorting, a task which requires focused attention, planning and control (Logie et al., 1994; Milner, 1963) and is thought to involve the central executive component of working memory. Logie, Gilhooly & Wynn (1994) found that random generation produced the largest disruption to arithmetic performance, suggesting that whilst it interfered with sub-vocal rehearsal (which maintains accuracy), it also interfered with the process responsible for calculation and estimation (the central executive) (Logie, Gilhooly & Wynn, 1994).
6.2.2 Cortical localization of working memory

Recently, there have been a number of studies attempting to localize the different components of working memory (e.g., Paulesu, Frith & Frackowiak, 1993; Coull, Frith, Frackowiak, & Grasby, 1996; see Smith & Jonides, 1997), with some apparent success in identifying the neural basis of the central executive. D’Esposito, Detre, Alsop, Shin, Atlas & Grossman (1995) compared activation (fMRI) for two non-working memory tasks (semantic-judgment requiring identification of exemplars of the category ‘vegetable’, and a spatial-rotations task) performed singly and under dual-task conditions. Compared to the single task condition, dual task performance showed bilateral dorsolateral prefrontal cortex (DLPFC) activation, suggesting that DLPFC “is involved in the allocation and coordination of attentional resources, a unique process observed by the CES [central executive system] component of working memory” (p.280). Anterior cingulate activation was also found for dual-task conditions, suggesting that the CES may comprise several neural components (D'Esposito, Detre, Alsop, Shin, Atlas & Grossman, 1995).

Dorsolateral prefrontal cortex has also been implicated in the processing of the contents of working memory (Smith, Jonides & Koepppe, 1996). Activation of dorsolateral prefrontal cortex was evident in a task requiring decisions about the identity (verbal condition) or location (spatial condition) of a letter presented three-back in a sequence of letters (Smith, Jonides & Koepppe, 1996). Such a finding is consistent with other studies suggesting that dorsolateral prefrontal cortex appears to be "routinely activated when computations must be performed on working memory" (p.18, Smith & Jonides, 1997).

In the present study, frontal excitation processes (as suggested by amplitude increases and latency decreases) was associated with unpracticed alphabet arithmetic (during the Algorithmic block), a task similar to unpracticed number arithmetic (Compton & Logan, 1991; Logan, 1988a), which shows evidence of counting and working memory processes (Ashcraft et al., 1992). Importantly, both Best and Worst performers showed response times for the Algorithmic task indicative of non-automatic processing, and both groups showed similar patterns of SSVEP topography during processing of the Alphabet Arithmetic equations, suggesting similarity of processing mechanisms.
Based on evidence of frontal activation for non-automatic tasks and the association of working memory with frontal activation, the slow response times by both groups of subjects and increased frontal activity during processing of the Alphabet Arithmetic equations is suggested to reflect the involvement of working memory during the Algorithmic block. This conclusion is supported by the results of a previous SSVEP study which suggested that increased amplitude and decreased latency in frontal regions was indicative of the utilization of working memory, being activation specifically related to maintaining for a short period of time (6 seconds) the spatial location of three targets (Silberstein, 1997).

### 6.2.3 Automatization and reductions in working memory utilization

It is apparent that working memory is utilized in complex, non-automatic arithmetic involving larger digits (Hitch, 1978a; 1978b; Ashcraft et al., 1992), but it is also evident that "even retrieval of the basic addition facts relies somewhat on working memory resources" (Ashcraft et al., 1992, Expt. 2, p.314). Arithmetic problems based on simple facts are negatively affected by concurrent tasks, but to a lesser degree than difficult problems, which are more adversely affected (Ashcraft et al., 1992). Thus, even in cases of automatic arithmetic performance, where a product or sum is retrieved from memory, the items to be summed or multiplied still need to be temporarily retained (Logie, Gilhooly & Wynn, 1994). This suggests a continuum of controlled processing or working memory involvement that diminishes with problem difficulty, such that “to the degree that component processes become automatic or autonomous, their reliance on working memory should become negligible" (p.314, Ashcraft et al., 1992). This is consistent with results suggesting that simple arithmetic in adults is performed at a level that is less than automatic (Zbrodoff & Logan, 1986; Ashcraft et al., 1992).

As such, working memory involvement in alphabet arithmetic, though expected to some degree at all stages of practice, would be expected to be highest during initial task performance, and to diminish with increasing levels of practice, as it does for number arithmetic (Ashcraft et al., 1992). This is the pattern of working memory utilization that is suggested by both the response time and SSVEP results for the Best performers.
6.3 Automatization block (A5) - performance after extended practice

For the Automatization block there were quite substantial differences between the two groups in both response time and SSVEP topography.

In contrast to the Best performers, the slow mean response times (>1300ms) of the Worst performers to the equations in the Automatization session (A5) were not consistent with automatic processing, and suggested that the Worst performers may still have been using calculation of answers (and therefore substantial working memory processes) on some or all of the trials, even after extended practice at the task. This is supported by the finding that during the Automatization session (A5), the Worst performers displayed a similar SSVEP topography to the Algorithmic block (specifically a frontal amplitude increase and latency decrease). The similarity between the Automatization and Algorithmic blocks of the Worst performers suggests that they preserved SSVEP components associated with Algorithmic processing, reflecting the possibility that they continued to use the initial mode of processing (counting) even after extended practice.

Conversely, the rapid response times of the Best performers (<800ms) for the Automatization block suggest that they were processing the stimuli in a different way than during the Algorithmic session, and this seems to be reflected in a differing SSVEP topography during the Automatization session. The decreased SSVEP amplitude after practice (during A5) for the Best performers was consistent with other studies showing reductions in brain activity after practice.

Haier et al. (1992) found an overall decrease in glucose metabolic rate with practice on the computer game Tetris, as well as specific decreases in left superior frontal cortex and left anterior cingulate. Dale, Halgren, Lewine, Buckner, Paulson, Marikovic & Rosen (1997) found that postero-ventral prefrontal cortex showed reduced activity to repeated stimuli. Casini & Macar (1996) found reduced activity in prefrontal cortex after practice at a time-interval (temporal) judgment task, whilst Petersen, Fox, Mintun & Raichle (1989) found that activity in the anterior cingulate gyrus and left inferior pre-frontal cortex was seen to diminish with practice at a verb-generation task. For another generate verbs task Raichle, Fiez, Videen, MacLeod, Pardo, Fox & Petersen (1994) found that whilst the naive (unpracticed) condition showed increased blood flow to the anterior cingulate, left prefrontal cortex and right cerebellar cortex, activation in the practiced condition was decreased in these areas.
Given that non-automatic arithmetic processing requires heavy utilization of working memory (Ashcraft et al., 1992), and that non-automatic Alphabet Arithmetic (during the Algorithmic block) was associated with increased SSVEP amplitude in frontal cortex (regions of which are thought to subserve the role of working memory) the reduced SSVEP amplitude in frontal regions during the Automatization block for the Best performers was interpreted as a reduction in the utilization of working memory.

This is consistent with previous findings of practice-related reductions in working memory utilization, suggested by reductions in dual-task interference effects with practice for arithmetic tasks (Ashcraft et al., 1992), and faster response times to highly practiced and single digit arithmetic problems compared to more complex problems (Ashcraft et al., 1992).

It is also consistent with one of the few studies that has investigated whether practice-related reductions in working memory utilization for arithmetic are reflected in psychophysiological measures. Pauli et al (1994) found that the amplitude of a late positive component decreased with practice at frontal sites, and this was suggested to reflect the decreasing use of calculation procedures. In a further study by Pauli et al. (1996), a similar frontal reduction in amplitude of a late positive component was interpreted as reflecting “very general information-processing processes...not specifically related to mental arithmetic” (p.528, Pauli et al., 1996).

An association between decreased utilization of working memory and automatization of arithmetic is supported by the finding that an external variable measuring working memory capacity was related to Numerical Facility and Perceptual Speed in a sample of grade school students but not for a college sample (Little & Widaman, 1992, cited in Widaman & Little, 1992). This suggests that working memory capacity has “an impact on ability performance at earlier ages, but not at later ages when these types of performance are more highly automatized” (Widaman & Little, 1992, p.236).

### 6.3.1 Different processing mechanisms for Best and Worst performers?

Although the Worst performers were consistently slower than the Best performers, and did not automatize, they showed a similar rate of reduction in response time as the Best performers. Both groups showed a power law decrease in
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response time with practice, which has been considered to be a 'benchmark' indication of skill acquisition and the development of automaticity (Newell & Rosenbloom, 1981; Logan, 1988a). However, previous findings have indicated that “similarity in performance improvement does not necessarily reflect similarity of processing mechanisms” (Dulaney & Rogers, 1994, Fisk, McGee & Giambra, 1988).

Dulaney & Rogers (1994) found that whilst old subjects were slower for Stroop colour-naming overall, both old and young subjects showed similar reductions in response time with practice. They suggested that improvements in performance of the Stroop task were due to the development of an automatic process (a reading suppression response) by the group of young subjects, and improvements in “effortful processes, such as general response and scanning strategies” (p.480), by the group of old subjects.

Similarly, in this study, the difference in response times between the Worst and Best performers may have been due to the use of different processing mechanisms in performing the Alphabet Arithmetic task, a possibility that appears to be supported by the SSVEP data.

For the Worst performers, the slow response times and similar SSVEP data in the Algorithmic and Automatization sessions suggests that the reduction in response time may have been due to an improvement in counting (controlled processing). On the other hand, in comparison with the Algorithmic block, the rapid response times and different SSVEP topography for the Best performers in the Automatization block was suggestive of a qualitatively different processing mechanism, likely to be automatic processing mediated by memory retrieval.

6.3.2 Increase in brain efficiency with learning?

The reduced excitation (inferred by reduced amplitude and increased latency) associated with Alphabet Arithmetic performance during the Automatization block shown by the Best performers is consistent with a 'brain efficiency' hypothesis of learning, suggested by Haier et al. (1992a; 1992b). They found decreased overall brain glucose metabolic rates after practice on the computer game Tetris, and suggested that this might reflect the use of fewer brain regions in performance of the task, and consequently, an increase in brain efficiency. Similarly, the results of this study (improved performance but less brain activity) suggest that automatic performance
produced by extended practice on the Alphabet Arithmetic task was associated with more efficient processing.

However, perhaps one of the most interesting findings of this study concerns the differences between the Best and Worst performers, and why the Worst performers did not automatize. Perhaps the Best performers had superior arithmetic capabilities to the Worst performers, allowing them to transpose those skills to the novel Alphabet Arithmetic task. This would explain the faster response times of the Best performers during the Algorithmic block, but not necessarily why the Worst performers appeared not to memorize the equations, nor use a memory-retrieval strategy.

An alternative explanation of these differences comes from findings on intelligence and performance on a problem-solving task (Raven's Advanced Progressive Matrices), and a perceptual-motor task (the computer game Tetris). Haier, Siegel, Nuechterlein, Hazlett, Wu, Pack, Browning & Buchsbaum (1988) found an inverse relationship between absolute glucose use and performance on the RAPM, a non-verbal test of abstract reasoning ability highly correlated with the WAIS and Spearman's g (Paul, 1985). They suggested that those subjects who found the task most difficult (low scorers) required more cortical activity to perform the task, as indicated by higher glucose utilization, possibly due to inefficient neural circuitry or the use of extraneous circuits. On the other hand, it was suggested that the high performers showed low glucose use because their neural circuits were more efficient and/or they were able to access the circuit most appropriate for solving the problem. A similar result was found by Haier, Siegel, Tang, Abel and Buchsbaum (1992b), who examined correlations between intelligence and changes in glucose metabolic rate associated with learning Tetris. They found that subjects with the highest RAPM scores showed the largest decreases in overall glucose metabolic rate and GMR in specific brain regions (including frontal areas) after learning, suggesting that "high-ability subjects may have the most gains in automatic processing" (p.425).

The results of this study parallel those findings, in that Best performers automatized and showed a greater decrease in brain activity with practice than Worst performers, who did not automatize. Given that in the Haier et al. (1992b) study, the high ability/intelligence subjects showed lower glucose metabolic rates after practice than the lower ability/intelligence subjects, the lower brain activity of the Best performers after practice may suggest that the performance differences between the
two groups were due to differences in intelligence. However, this can remain only speculation since intelligence was not measured in this group of subjects.

6.4 Inhibitory processes in cognition

The automatic processing exhibited by the Best performers was associated with markedly reduced SSVEP amplitude and increased latency (relative to their Algorithmic performance), and was suggested to reflect reduced brain activity. Another possibility suggested by these findings is that the reduced frontal SSVEP amplitude after practice may not only have reflected a decrease in excitation, but also an increase in inhibition. Inhibition is suggested to occur simultaneously with, and to mediate excitation in the brain (Houghton & Tipper, 1996; Clark, 1996) and importantly, inhibitory processes have been suggested to play a role in learning and improvements in performance with practice (Harnishfeger & Bjorklund, 1994; see Eccles, 1977).

Recently, there has been increasing interest in the role that inhibition may play in mediating cortical activity and human behaviour (see special edition of Brain & Cognition, v.30, 1996), and Clark (1996) has suggested that both inhibition and excitation form “essential building blocks” (p.131) in the understanding of a myriad of human cognitive and behavioural phenomena.

However, before proceeding, it is necessary to clarify just what is meant by the term 'inhibition'. It is evident that there are a number of different levels (neuronal, cognitive or behavioural) at which inhibitory mechanisms can act (Clark, 1996), and the term 'inhibition' has tended to be used to refer to all these situations. However, it is probably desirable to be more specific about the nature of these inhibitory processes. For example, in the memory literature, the term inhibition appears to be used in two senses; a 'weak' sense, referring to effects that are the opposite of facilitation (i.e., decreases in recall performance), and a 'strong' sense, referring to a reduction in the activation level of an internal representation by an inhibitory mechanism (Anderson & Bjork, 1994).

To this end, this section of the discussion will refer to inhibition in the two senses outlined by Anderson & Bjork (1994), with inhibition at a cellular or neurophysiological level being included in the 'strong' category.
6.4.1 'Strong' inhibition and electrophysiology

Recently, there has been a move towards establishing whether inhibition in the 'weak sense' reflects inhibitory processes in the 'strong sense' (see Clark, 1996; Houghton & Tipper, 1996; Anderson & Bjork, 1994), since many 'weak sense' inhibition effects can be explained without invoking actual inhibitory mechanisms (Anderson & Bjork, 1994).

However, direct quantification of neuronal inhibitory processes is not yet possible, since current imaging technologies measure increased metabolic activity generated primarily by the pyramidal cells (Jones, 1984; Douglas & Martin, 1990). Nonetheless, inhibition has been inferred from some electrophysiological results, such as decreased activation of single-cells to unattended stimuli in visual cortex and inferior temporal cortex (Moran & Desimone, 1985; Wurtz et al., 1984), and increasing correlations between evoked potentials to patterned and unpatterned stimuli in older subjects, which is consistent with the idea of a reduction in inhibitory function with age (Dustman, Emmerson & Shearer, 1990).

It has also been suggested that whilst scalp surface-negative potentials generated by “depolarization in the apical dendritic trees of pyramidal cells” (p.236, Rockstroh, Muller, Wagner, Cohen & Elbert, 1993) may reflect increased cortical excitability, positive potentials have been suggested to reflect a lowering of cortical excitability, or inhibition of neuronal networks. This hypothesis comes from studies observing a correspondence between negative slow cortical potentials and response facilitation (Rockstroh et al., 1993; see Rockstroh, Elbert, Canavan, Lutzenberger & Birbaumer, 1989), and other studies showing inhibition of behavioural and electrophysiological responses associated with positive potentials (Roberts, Rau, Lutzenberger, & Birbaumer, 1994; Rockstroh, Muller, Cohen & Elbert, 1992).

Rockstroh et al. (1993) used the onset and offset of a diffuse visual stimulus to elicit a CNV (contingent negative variation), and then presented auditory clicks as probes before, during and after the visual stimulus. They found that motor responses were faster, and the amplitude of the N1/P3 peak-to-peak evoked potential were larger to the clicks presented during the time-course of the CNV than to clicks presented before the visual stimulus. It was suggested that the CNV reflects an increased cortical excitability which facilitates processing of probe stimuli because the cortical network is already excited/activated.
On the other hand, Rockstroh et al. (1992) presented probe stimuli at different delays after standard and P300-eliciting target stimuli in an auditory oddball paradigm. They found that for subjects who developed an oddball P300, motor responses were slower and probe evoked potentials were smaller in amplitude when the probe was processed during the presence of the P300, supporting the hypothesis that positivity reflects reduced excitability of neuronal networks. Similarly, Roberts, Rau, Lutzenberger, & Birbaumer (1994) found augmentation of P300s for No-Go compared to Go stimuli in a continuous performance (“OX”) task, associating the larger P300s elicited by No-Go stimuli (“O-not X”) with suppression of prepared motor responses.

In relation to cognitive processes, in particular mental arithmetic, negativity of ERP's has been associated with conscious, non-automatic performance associated with complicated mental arithmetic tasks, such as dividing a 3-digit number by seven and computing the remainder (Ruchkin, Johnson, Canoune & Ritter, 1991).

Conversely, positivity has been associated with automatic performance of arithmetic tasks. Pauli et al. (1994) investigated changes in a P300-like evoked potential with practice on a simple mental multiplication task, and found consistent positivity in parietal regions at all stages of practice, suggesting the necessity of this region to mental arithmetic. This positive component rebounded and became a slow negative wave, showing greater negativity prior to response for difficult problems and a decrease in that negativity with practice. It was suggested that the consistent parietal positivity reflected retrieval of arithmetic facts from cortical networks, specifically the inhibition of multiple incorrect problem-answer associations, whilst the negativity prior to response was suggested to reflect mediating strategies initiated late in processing, consistent with findings that negativity is associated with conscious awareness of mental processes (Libet, 1985). Similar results regarding positivity were found by Pauli et al. (1996), but the polarity of the EP prior to response was positive rather than negative. It was suggested that this reflected the automatic nature of processing in the task, and that the pre-response negativity observed by Pauli et al. (1994) reflected non-automatic processing that may have been the result of insufficient training.
6.4.2 'Strong' inhibition and the SSVEP

There is no known direct relationship between polarity of scalp ERP's and the dynamics of the SSVEP, and so although inhibition is implicated in automatic arithmetic performance by positive potentials, it is uncertain as to how inhibition may manifest itself in the SSVEP. Certainly, given that a decrease in SSVEP amplitude is suggestive of decreasing activity, such a reduction may reflect increased inhibition, although it most likely reflects the simultaneous occurrence of both inhibition and decreased excitation (see p.129, Clark, 1996).

Whilst the amplitude reduction seems to fit with the conception of an increase in inhibition, explaining the increased latency is not so straightforward. However, an association between increased SSVEP latency and inhibition is consistent with a model of neocortical dynamics proposed by Silberstein (1995b; 1998).

Many regions of cortex are hierarchically related to each other and connected in a reciprocal fashion, an example of which is the relation between the visual striate cortex and visual association cortex (Silberstein, 1995b). According to this model (Figure 6.1), the reciprocal connections between primary and association cortices provide for 'feed-forward' loops, originating mainly in Layers 2 & 3 and which synapse predominantly in Layer IV, and 'feedback' loops, originating mostly in Layers 5 & 6 and synapsing mainly in Layer I.

Figure 6.1 Feed-forward and feedback connections between cortical layers (from Silberstein, 1998)
With inhibitory feedback mediated predominantly by Layer I, such connections between regions suggests the possibility of resonance processes existing within such structures (Silberstein, 1995b), with resonant frequencies determined by axonal (propagation) and synaptic delays (Silberstein, 1998). These resonances are referred to as 'regional resonances', and are suggested to possibly be the origin of EEG rhythms with frequencies less than 20Hz (Silberstein, 1995b). As such, the 13Hz activity measured in this study is likely to reflect such regional resonances.

These 'resonances' depend upon transmission speed within the loops, which is determined by facilitation and inhibition of the feed-forward and feedback connections. “High transmission efficiency in layers I and IV simultaneously will enhance regional resonances, while inhibition of layer I inputs will reduce or eliminate regional resonances” (p.36, Silberstein, 1997). Specifically, facilitation leads to increased efficiency of transmission (reduction in synaptic delays and increased propagation speed), manifested as a decrease in SSVEP latency. Conversely, inhibition leads to increased synaptic delays and reduced propagation speed, and manifests itself as an increase in SSVEP latency.

Therefore, the increased SSVEP latency in frontal regions would seem to suggest that inhibitory processes were involved in automatic alphabet arithmetic performance exhibited by the Best performers, consistent with suggestions that inhibition is involved in automatic performance of arithmetic tasks (see Pauli et al, 1994; 1996).

6.4.3 Speculation on inhibitory processes in alphabet arithmetic

The suggestion of a role for inhibitory processes in Alphabet Arithmetic performance is also consistent with modern models of arithmetic processing.

Arithmetic shows a transition from counting to remembering that reflects the build-up of information in memory, such that automatic performance of number arithmetic requires selection and retrieval of facts from memory (Ashcraft, 1992; Campbell & Oliphant, 1992). Evidence of priming effects and models of arithmetic performance suggest that arithmetic facts are associatively or semantically related to each other in memory, that multiple facts are activated in memory by presentation of a problem, and that automatization reflects the increasing inter-association of those facts (Campbell, 1987; Campbell & Arbuthnott, 1996). "A common view is that normal
adults have available a vocabulary of known sums, products, and so on, which are organized in the form of an associative network that capitalizes on the brain mechanisms involved in processing language” (p.395, Logie et al., 1994). As such, semantic retrieval processes are implicated in simple arithmetic performance.

A number of memory models draw an analogy between memory retrieval and selective attention (Houghton & Tipper, 1994; 1996; Carr & Dagenbach, 1990), arising from the observation that both selective attention and memory retrieval require the "isolation of a mental representation of one object or piece of information from among a set of activated alternatives" (Anderson & Bjork, 1994, p.303). Even though selective attention is more often “associated with selection amongst competing perceptual contents” (Houghton & Tipper, 1996, p.21; Keele & Neill, 1978), such a construct can also be equated with a cognitive control mechanism that allows for the selection of one representation from many parallel activations (p.20-21, Houghton & Tipper, 1996).

Now, in selective attention, the negative priming effect (see Tipper, 1985; Houghton & Tipper, 1996) and findings of reduced single cell responses to unattended stimuli in visual cortex and inferior temporal cortex (Moran & Desimone, 1985) have suggested the existence of an inhibitory or suppression mechanism.

As such, memory inhibition models advocating an attentional suppression mechanism suggest that "semantic retrieval involves processes highly similar to those that underlie selective attention, perhaps including suppression of internally-generated competing responses analogous to the externally-presented distractors in selective attention.” (p.137, Clark, 1996).

A role for inhibitory processes in semantic retrieval in non-arithmetic domains has been implied by a number of empirical findings, such as retro-active interference effects, whereby retrieval of paired-associate-responses to words in an initial list is suppressed by the same stimuli in a second list (Winocur, Moscovitch & Bruni, 1996), and retrieval blocking, whereby using half of the words in a list as cues blocks retrieval of other words in that same list (Roediger & Neely, 1982). It is also implied by uncertainty effects, in which naming of pictures with multiple labels is slower than naming of single-label pictures (Lachman, 1973; Paivio et al., 1989), suppression of irrelevant meanings of homonyms in selective attention (Marcel, 1980) and sentence comprehension (Gernsbacher & Faust, 1991), and the disruption of
recognition of phonetically similar auditory targets by auditory primes (Goldfinger et al., 1992).

Importantly, just as inhibition is implicated in semantic retrieval in these domains, inhibitory processes have been implicated in the retrieval of number facts by the phenomenon of negative error priming (Clark, 1996; see Campbell & Clark, 1989, Campbell & Arbuthnott, 1996).

Error priming is thought to reflect excitatory and inhibitory processes in memory retrieval of arithmetic facts (see Campbell & Oliphant, 1992). Negative error priming refers to situations in which the probability that a previous answer will be produced incorrectly as the answer to any following trial is less than chance, and occurs for the trial immediately following presentation of a particular fact. Positive error priming refers to situations in which the probability that a previous answer will be produced incorrectly as the answer to any following trial is greater than chance, and occurs for 2-10 trials after presentation. Positive priming is suggested to reflect excitation due to residual activation and to be indicative of answer retrieval processes (Campbell, 1991), whereas negative error priming is suggested to reflect inhibition (which serves to counter-act the interference between adjacent trials caused by residual excitation) and "reduced accessibility of answer retrieval or production processes" (pp.167-168, Campbell & Tarling, 1996).

Negative error priming has been observed in arithmetic production tasks, which involve retrieval of an answer from memory (Campbell, 1987; Campbell & Arbuthnott, 1996). Verification was thought to involve retrieval (see Ashcraft & Battaglia, 1978), but certain findings (see Ashcraft & Stazyk, 1981) suggest that verification may involve other mechanisms, perhaps based on plausibility judgments (Kreuger, 1981) or familiarity of answers (Zbrodoff & Logan, 1990).

However, there is evidence that retrieval may be involved in processing True verification equations. Response times to True verification equations are generally faster than to False verification equations (Ashcraft & Stazyk, 1981), and Campbell (1987) found that presenting the correct answer as a prime has facilitatory effects on response time in multiplication verification, and appears to pre-activate the answer in memory. Also, Campbell & Tarling (1996) found stronger positive error priming of production errors by True verification trials compared to False verification trials when they alternated verification and production trials. This led the authors to suggest that
retrieval of answers for True production problems may be primed by presentation of that correct answer in a preceding verification trial.

Nevertheless, Campbell & Tarling (1996) emphasize that a variety of factors may mediate the relative contribution of familiarity or retrieval-based processes in verification. In particular, they suggested that an emphasis on speed would promote a familiarity-based approach, since "familiarity information will often be available more quickly than a specific answer" (p.170, see Reder & Ritter, 1992), but that retrieval will be promoted when True and False equations are difficult to discriminate from each other, and when accuracy is emphasised.

Given that alphabet arithmetic shows a similar transition from counting to remembering as number arithmetic, it does not seem unlikely that an associative network for alphabet arithmetic facts may develop, similarly to that which is suggested to develop for number arithmetic. Therefore, given that performance of True number arithmetic verification problems involves memory retrieval, and that inhibitory processes may play a part in selecting the answer from the set of activated nodes in memory, it is possible that inhibition may also be involved in Alphabet Arithmetic involving retrieval, provided that the task conditions are conducive.

In the case of verification alphabet arithmetic in this study, only trials containing True equations were analysed, and automatic alphabet arithmetic involving those equations appeared to be mediated by memory retrieval. Furthermore, True and False equations were difficult to distinguish from each other, having only ±1 difference between correct and incorrect answers. Also, accuracy was apparently not sacrificed for speed, as shown by relatively high accuracy levels (~90%) and an increase in both speed and accuracy with practice. Thus, the task conditions for this Alphabet Arithmetic task seem to fit those conditions suggested by Campbell & Tarling (1996) to promote memory retrieval for True number arithmetic equations.

Therefore, given that automatic number arithmetic occurs via memory retrieval and involves an inhibitory mechanism similar to that proposed for selective attention, the similarities between alphabet arithmetic and number arithmetic suggest that similar inhibitory processes may also be involved in Alphabet Arithmetic.
6.4.4 Inhibition and differences in performance

The non-automatic performance of the Worst performers after extended practice suggested that task performance was not mediated by memory retrieval. If we accept that the automatic performance of the Best performers showed evidence of inhibitory processes, then the SSVEP data associated with the practiced Alphabet Arithmetic of the Worst performers suggests that the involvement of inhibition was lower.

As such, the results are consistent with evidence suggesting that whilst inhibition appears to become more efficient with maturation, it can also become more efficient through the development of skill (see Harnishfeger & Bjorklund, 1994; Clark, 1996), such that "individual differences in cognitive inhibition contribute significantly to individual differences in cognitive performance" (p.346, Harnishfeger & Bjorklund, 1994). For example, Gernsbacher, Varner & Faust (1990) found that adults showing greater comprehension of verbal, non-verbal and written stories were better able to suppress inappropriate meanings of ambiguous words, and as such were better able to suppress irrelevant information. Similarly, Gernsbacher & Faust (1991) found that more skilled comprehenders were better able to suppress contextually incorrect homophones.

It has been also suggested that in the case of simple arithmetic, whereby a criterion level of activation must be reached before memory retrieval is used as an effective alternative to counting (following Siegler, 1988; but see also Campbell & Oliphant, 1992), inefficient inhibition will lead to multiple activations in memory reaching threshold and subsequent impulsive, incorrect responding (Harnishfeger & Bjorklund, 1994). On the other hand, it could also lead to low levels of activation for all alternatives, and consequently, the use of a slower, more effortful method of obtaining the answer, such as counting (Harnishfeger & Bjorklund, 1994).

Relating this suggestion to this study, the Worst performers appeared to retain a counting strategy even after practice, whilst the Best performers changed to a memory retrieval strategy. This transition from counting to memory retrieval in adults for alphabet arithmetic parallels the transition from counting to remembering in children for number arithmetic, and this transition appears to parallel the growth in efficiency of inhibitory function (see Ashcraft et al., 1992). Given that young children tend to maintain a counting strategy and presumably possess inefficient inhibitory
mechanisms, it seems possible that the Worst performers in this study also exhibited inefficient inhibition, requiring them to use counting to obtain the correct answers to the alphabet arithmetic task. This possibility is supported by the response time data (revealing non-automatic processing even after extended practice), and the SSVEP data suggesting that inhibition was not involved in the Worst performers practiced alphabet arithmetic (unlike the Best performers).

6.5 Conclusions

6.5.1 Summary

Automatization of alphabet arithmetic in this study was associated with a reduction in response time that followed a power law, a finding consistent with those of Logan and colleagues (Logan, 1988a; Logan & Klapp, 1991; Klapp, Trabert, Boches & Logan, 1991), and previous findings on skill development and automatization (see Newell & Rosenbloom, 1981).

It is suggested that unpracticed, novel performance of alphabet arithmetic required substantial working memory involvement, and therefore significant activity in frontal brain regions thought to subserve this role, and was reflected in increases in the increased amplitude and reduced latency of scalp-recorded SSVEP over those regions. On the other hand, automatization of alphabet arithmetic was associated with a reduction in SSVEP indicators of working memory processes, reflected in a decrease in frontal SSVEP amplitude and increased latency.

Performance-based separation of the subject pool suggested that Worst performers, characterised by high response times, increased SSVEP amplitude and decreased latency, appeared to have continued to utilize algorithmic processing, even after extensive practice. Conversely, based on the low response times of Best performers for the Automatization session, it is suggested that automatic performance of alphabet arithmetic performance was associated with memory retrieval processes, reflected in decreased SSVEP amplitude and increased latency.

Furthermore, it is suggested that this reduction in SSVEP amplitude and increased latency may reflect inhibitory processes implicated in semantic memory retrieval, similar to those proposed to operate in selective attention.
6.5.2 Limitations

A number of factors may have limited the findings in the current study. Whilst this study showed changes in activation in frontal regions, consistent parietal activation during performance of the task was not apparent. Both the Best and Worst performers did show a significant difference in latency and amplitude in the left parietal region during the Algorithmic block (AL) (Results, Fig. 5.15), but it appeared to decrease with practice such that there was little parietal activity observed during the Automatization block (A5), a finding which contrasts with previous work showing consistent parietal activation for tasks involving arithmetic and access to numbers (Roland & Friberg, 1985; Ruchkin et al., 1991; Dehaene, Dehaene-Lambertz & Cohen, 1998), even after extended practice (Pauli et al., 1994; Pauli et al., 1996).

However, it may be that the use of an arithmetic task as the reference resulted in the canceling out of this parietal activation because of the utilization of a subtraction methodology, which removes components common to the reference and task of interest. Consequently, the level of parietal activation during the Automatization block (A5) would have been similar to the reference (mean amplitude and latency of A5), and so would not be observed in the topographic difference maps shown in the Results section. Accordingly, the utilization of a non-arithmetic reference task may have overcome this limitation.

A further limitation related to the response time-addend relationship between the equations. The purpose of the study was to observe the transition from algorithmic to automatic processing, and practice was designed to allow for the development of automatization within the period of recording. Since the most important factor in automatization has been shown to be the number of times an individual stimulus is encountered (Logan & Klapp, 1991), this necessitated a maximising of the number of presentations of individual stimuli by making the task self-paced and using a small number of equations.

However, a number of side-effects of this were evident. The small number of addends (+3 and +4) did not yield a response time-addend relationship of the same magnitude as that evident in previous studies of alphabet arithmetic (Logan, 1988a) and number arithmetic (Groen & Parkman, 1972). In fact, after the Algorithmic block, no discernible response time-addend relationship was evident, but rather, a relationship between each individual equation and response time became noticeable,
with no particular relation between equation type (H vs. T, 3 vs. 4). Although this facet of the results would seem to suggest that the Worst performers were not counting, the slowness of their response times suggests that they were not using memory retrieval processes. It appears that the Worst performers continued counting, but that the small number of addends (+1 or -1) prevented the expected response time-addend relationship.

On the other hand, for the Best performers, the small number of addends may have allowed for the rapid development of stimulus-response pairings in memory and the use of memory retrieval on at least some trials at a relatively early stage of the task. This explanation is consistent with the finding that automaticity could be produced for a small number of Alphabet Arithmetic facts in less than 15 minutes using memorization (Logan & Klapp, 1991).

A larger number of addends (+2, +3, +4, & +5) may have provided a better response time-addend relationship, but the small number of equations was unavoidable, given the short time required to complete recording of each subject and to facilitate the transition from novice to expert within that time.

Another problem was that the self-paced nature of the task led to differing amounts of practice for fast and slow subjects. Computer pacing of the task may have avoided the practice differential, but at the expense of insufficient time to respond for poor performers initially, and boredom at later stages of practice for better performers. It would be interesting to observe whether slow subjects would have shown similar response times (and perhaps even similar SSVEP responses) had they experienced the same number of presentations of individual stimuli as fast performers. However, these differences are what is perhaps most interesting about these findings. Why were some subjects slower than others? Does this reflect an underlying difference in arithmetic abilities, working memory capacity, or perhaps a difference in cognitive flexibility required in learning new tasks?

6.5.3 Suggestions for further work

Alphabet arithmetic is similar to number arithmetic and is a relatively novel task for adults, and as such, is well placed to provide information on the processes underlying the development of automatic performance in simple arithmetic, and
therefore perhaps to also reflect on the development of automatic processing in other domains, as well as on the more general role that memory plays in automatization.

Avenues of further research into automatization of alphabet arithmetic could include an examination of the effects on SSVEP topography of introducing new equations after learning of a different set has already occurred. A rebound effect for response time would be expected (see Schneider & Shiffrin, 1977), and it would be interesting to note whether similar effects were observed for the SSVEP components (i.e., an increase in amplitude and decrease in latency).

A further facet to this study could be an examination of whether a correlation exists between the magnitude of SSVEP components and response time; that is, do the SSVEP decreases in amplitude and increases in latency follow a power law similar to the power law decrease in response time.

Furthermore, given recent attempts to integrate findings of cognitive inhibition with neurophysiological inhibitory processes, future studies could perhaps use an alphabet arithmetic production task, which would circumvent the question of whether verification involved memory retrieval processes. If combined with new imaging technologies, such an approach may be able to shed further light on the nature of inhibition in semantic retrieval, and the relationship between cognitive or behavioural (‘weak’) and neurophysiological (‘strong’) inhibition.
Appendix A

Table A.1

Mean Number of Trials of Equations Completed during each Block

<table>
<thead>
<tr>
<th>Block</th>
<th>All Subjects</th>
<th>Best Performers</th>
<th>Worst Performers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithmic</td>
<td>31</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td>Automatization 1</td>
<td>57</td>
<td>64</td>
<td>54</td>
</tr>
<tr>
<td>Automatization 2</td>
<td>74</td>
<td>86</td>
<td>65</td>
</tr>
<tr>
<td>Automatization 3</td>
<td>85</td>
<td>95</td>
<td>70</td>
</tr>
<tr>
<td>Automatization 4</td>
<td>87</td>
<td>100</td>
<td>74</td>
</tr>
<tr>
<td>Automatization 5</td>
<td>92</td>
<td>109</td>
<td>77</td>
</tr>
</tbody>
</table>

Table A.2

Mean Accuracy for True Equations

<table>
<thead>
<tr>
<th>Task Block</th>
<th>All Subjects</th>
<th>Best Performers</th>
<th>Worst Performers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithmic</td>
<td>86.01 %</td>
<td>87.29%</td>
<td>85.69%</td>
</tr>
<tr>
<td>Automatization 1</td>
<td>87.45 %</td>
<td>84.83%</td>
<td>87.36%</td>
</tr>
<tr>
<td>Automatization 2</td>
<td>90.25 %</td>
<td>91.01%</td>
<td>88.74%</td>
</tr>
<tr>
<td>Automatization 3</td>
<td>92.10 %</td>
<td>92.87%</td>
<td>89.62%</td>
</tr>
<tr>
<td>Automatization 4</td>
<td>92.71 %</td>
<td>93.61%</td>
<td>90.67%</td>
</tr>
<tr>
<td>Automatization 5</td>
<td>93.93 %</td>
<td>93.38%</td>
<td>93.03%</td>
</tr>
</tbody>
</table>

Table A.3

Difference in Mean Response Time between +3 and +4 Addend Equations

<table>
<thead>
<tr>
<th>Block</th>
<th>+3 Equations</th>
<th>+4 Equations</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithmic</td>
<td>2897ms</td>
<td>3044ms</td>
<td>+147ms</td>
</tr>
<tr>
<td>Automatization 1</td>
<td>1859ms</td>
<td>1879ms</td>
<td>+20ms</td>
</tr>
<tr>
<td>Automatization 2</td>
<td>1444ms</td>
<td>1439ms</td>
<td>-5ms*</td>
</tr>
<tr>
<td>Automatization 3</td>
<td>1176ms</td>
<td>1179ms</td>
<td>+3ms</td>
</tr>
<tr>
<td>Automatization 4</td>
<td>1076ms</td>
<td>1090ms</td>
<td>+14ms</td>
</tr>
<tr>
<td>Automatization 5</td>
<td>1015ms</td>
<td>998ms</td>
<td>-17ms*</td>
</tr>
</tbody>
</table>

(* denotes blocks where mean response time for +4 equations was faster than mean response time for +3 equations)
### Table A.4

**Difference in Mean Response Time for H-based and T-based Equations for each Automatization Session.**

<table>
<thead>
<tr>
<th>Block</th>
<th>H Equations</th>
<th>T Equations</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automatization 1</td>
<td>1872ms</td>
<td>1865ms</td>
<td>-7ms</td>
</tr>
<tr>
<td>Automatization 2</td>
<td>1466ms</td>
<td>1415ms</td>
<td>-51ms</td>
</tr>
<tr>
<td>Automatization 3</td>
<td>1198ms</td>
<td>1159ms</td>
<td>-39ms</td>
</tr>
<tr>
<td>Automatization 4</td>
<td>1109ms</td>
<td>1057ms</td>
<td>-48ms</td>
</tr>
<tr>
<td>Automatization 5</td>
<td>1023ms</td>
<td>988ms</td>
<td>-35ms</td>
</tr>
</tbody>
</table>

### Table A.5

**Mean Response Times to +3 and +4 Equations for Best and Worst Performers**

<table>
<thead>
<tr>
<th>Task Block</th>
<th>Best Performers</th>
<th>Worst Performers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+3</td>
<td>+4</td>
</tr>
<tr>
<td>Algorithmic</td>
<td>2446ms</td>
<td>2660ms</td>
</tr>
<tr>
<td>Automatization 1</td>
<td>1492ms</td>
<td>1481ms*</td>
</tr>
<tr>
<td>Automatization 2</td>
<td>1145ms</td>
<td>1115ms*</td>
</tr>
<tr>
<td>Automatization 3</td>
<td>920ms</td>
<td>922ms</td>
</tr>
<tr>
<td>Automatization 4</td>
<td>817ms</td>
<td>824ms</td>
</tr>
<tr>
<td>Automatization 5</td>
<td>761ms</td>
<td>768ms</td>
</tr>
</tbody>
</table>

(*) denotes blocks where mean response time for +4 equations was faster than mean response time for +3 equations)
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