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# Transfer of automatic skills: the role of automaticity in skill acquisition and transfer

Katrina Louise Muller-Townsend
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Transfer of Automatic Skills: the Role of Automaticity in Skill Acquisition and Transfer


Katrina Louise Muller-Townsend, B.A (Psychology) Hons


School of Arts and Humanities

Psychology

Edith Cowan University


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Principal Supervisor: Professor Craig P. Speelman

Associate Supervisor: Dr Guillermo Campitelli

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# Abstract

Skill acquisition theories suggest that automaticity of lower-level processes is required before the acquisition of higher-level skills can be attempted. However, there is a disparity between the theoretical expectations of skill acquisition and the empirical findings in the transfer of training research. Research has found that when a change is made to the contextual conditions in which a skill is acquired, the learned response becomes less skilled. When skill transfer occurs performance is disrupted so that reaction times are slower than observed prior to the context change. This observation has been made with several different tasks, however no research has established whether a transfer disruption is observed with automatic skills. The discrepancy between the theoretical assumptions and empirical findings suggests that aiming for automaticity in education may not be best practice. The experiments in the current thesis were designed to examine whether automaticity disrupts or enhances transfer performance. The studies were based on Lassaline and Logan's (1993) visual numerosity task and Speelman and Parkinson's (2012) two-step task design. The study has a particular emphasis on individual differences, and thus individual participant data are explored to determine the pervasiveness of trends observed in the group data. In experiment one it was found that experimental design might play a role in the acquisition and probability of transfer, with the experimental conditions revealing differences in disruption and acquisition of automaticity. Group results in experiment two suggest that automaticity is unaffected by context changes, however individual results revealed that some participants failed to approach automatic performance. In experiment three participants were approaching automaticity, however a large percentage of participants did not demonstrate a shift from controlled to automatic processing. Furthermore, group results suggest that performance is unaffected by context changes in transfer, yet, this observation was not reliably presented amongst individuals with many individuals demonstrating transferable skills while not

attaining automaticity. Overall, the results appear to be congruent with Lassaline and Logan's (1993) findings. According to the group data, automaticity appears to facilitate transfer, and performance continues in accordance with the power law of learning; automaticity was transferred despite novel context changes. However, individual data indicates that not all participants are behaving this way. The current results question whether automaticity should be the desired outcome in education settings as many people failed to achieve automaticity. Further research is required at an individual level that includes factors such as working memory ability and task approach to determine why some participants deviate way from group data trends, and why they may be affected differently by context changes.

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# Chapter 1: Introduction

Automatic skills are a fundamental part of everyday functioning. The instant coming-to-mind of familiar knowledge when we need it is a well-known phenomenon (Logan, 1988). There are many human processes that can occur automatically, such as driving a car or recalling times tables. What is of interest in this thesis is what happens to automatic skills when changes are made to the performance context. For example, if someone has learned to drive a car with an automatic transmission, and has mastered the accelerator and brake pedals, when the driver attempts to transfer this knowledge to a car with manual transmission, in some respects the driver becomes a novice, once again having to coordinate acceleration and braking with the introduction of the clutch. Several theories [e.g., the adaptive control of thought (ACT) theory (Anderson, 1982, 1987); procedural reinstatement theory (Healy, Kole, & Bourne, 2014; Healy, Wohldmann, Parker, & Bourne, 2005); the instance theory (Logan, 1988, 2002); transfer appropriate processing (Morris, Bransford, & Franks, 1977; Weldon, Roediger & Challis, 1989); and identical elements theory (Singley & Anderson, 1989)] describe the conditions under which transfer between skills can occur, but none of these theories adequately explain what happens when a skill has become automatic and knowledge is applied beyond the context in which it was acquired. There is little research on the specific question of whether automaticity facilitates or hinders transfer.

The question of whether transfer is facilitated or inhibited by automaticity presents a conundrum in education: should learners strive for automaticity in order to facilitate flexible transferrable skills, or does automaticity hinder successful skill transfer due to the rigid, inflexible, context bound nature of automatic skills? The importance of the issue has been highlighted by contrasting and alternative theoretical interpretations: transfer may be facilitated by automaticity, or, transfer may be inhibited by automaticity (discussed further in Chapter 4). Skill acquisition theories, such as the ACT (Anderson, 1982, 1987) and instance

theory (Logan, 1988) cannot justify either position due to the lack of research directly addressing transfer of automatic skills. Many transfer of training studies have investigated the constraints in which transfer will or will not occur. Some (e.g., Lassaline & Logan, 1993; Logan, 1988) conclude that automaticity diminishes under transfer conditions involving context changes. The first objective in this thesis is to determine whether automaticity affects the transferability of learned skills in a primary task when context changes are made to a secondary task.

Skill acquisition theories suggest that effective and efficient learning requires automatic recall or 'automaticity' of component parts (discussed further in Chapter 3). Accordingly, automaticity is considered an essential factor in learning to master basic level skills before moving on to more complex skills (Chase & Simon, 1973; Logan, 1985). For example, students are often trained on arithmetic facts, such as multiplication, so that they can be automatically retrieved in order to free up cognitive load before attempting harder math combinations (Baroody, Bajwa, & Eiland, 2009; Cumming & Elkins, 1999) (discussed further in Chapter 2). Furthermore, when automaticity occurs, skill transfer has been demonstrated to occur beyond the conditions of which a skill was acquired (e.g., Anderson, 1982). Yet, there is a lack of empirical evidence to support a view that transfer is explicitly facilitated by automaticity. Educational research (i.e., Baroody et al., 2009; Cumming & Elkins, 1999) advocates that it is essential to attain automaticity with basic literacy and numeracy skills in order to develop higher-level cognitive skills; however, this assumption appears to be based only on inference. To date no studies have considered whether fundamental numeracy skills have been developed to automaticity or how this might affect (or limit) achievement in the long term.

There appears to be an implicit argument that practice, leading to automaticity of task components, enables transfer of skills when context or items do not deviate too much from

practice conditions. Although, this assumption of striving for automaticity is accepted and widely practiced in mainstream education and training, this does not seem to be the case in all research scenarios (e.g., Healy et al., 2005; Speelman, Forbes & Giesen, 2011; Speelman & Kirsner, 2001; see Chapter 4), nor is it justified by all theoretical explanations (see Chapters 2 and 3). This presents the current question under investigation: in requiring skills to become automatic before moving on in task complexity, are we in fact surpassing the optimum time for learning? On one hand, automaticity may produce flexible skills that can withstand changes in context, but on the other, automaticity could lead to inflexible skills that are difficult to moderate, leading to a disruption in performance.

The second objective of the studies reported in this thesis was to examine transfer performance beyond what might be displayed as an initial performance disruption. Specifically of interest is how performance is affected beyond the initial readjustment to context changes. Speelman and colleagues (i.e., Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2012) express this as an 'overhead' in performance reconceptualisation. Speelman and colleagues have found that when a change is made to the contextual conditions in which a skill is acquired, the learned response becomes less skilled. Skill transfer occurs, but performance is disrupted so that reaction time (RT) becomes slower than observed prior to the context change. It is expected that with any change to a task or surrounding context there will be a slight increase in RT performance as participants readjust to the environment changes; however, performance after the initial disruption may determine whether automaticity affects or reflects skill transfer. The observation of transfer has been made with several different tasks, yet no research has established whether automaticity affects the transferability of skills. Although skill acquisition theories describe automaticity as the end point of skill acquisition, the extent to which automaticity affects transfer is unclear. The discrepancy between assumed theoretical interpretations and empirical findings

further questions whether striving for automaticity is in fact the best learning practice. Furthermore, there is a lack of evidence to support the value of a lengthy learning process of waiting for basic skills to become automatic before moving on in task complexity.

The rationale for the experimental design used in this thesis was derived from a review of earlier work by Lassaline and Logan (1993), and that of Speelman and Parkinson (2012). Lassaline and Logan utilised a visual numerosity task, in which participants were presented with a configuration of dots, ranging in number from six to 11, on a computer screen, and were asked to report the number of items by pressing the corresponding keys on the response pad. The time taken to respond was a function of the number of dots presented on screen. Lassaline and Logan found that after 1920 trials (64 repetitions per item) the relationship between the number of items on screen and response times disappears, thus a change in strategy from a counting algorithm (controlled process) to memory strategy (automatic retrieval) could be inferred. Although Lassaline and Logan also reported that successful transfer can occur between items learned in training to altered transfer tasks, so long as item changes do not deviate too much from the original training task, they only considered transfer performance from one session, and did not evaluate the effect of transfer beyond what may be considered a re-evaluation of new task conditions. This may not provide enough insight into the nature or recovery of transfer performance. Further to this, Lassaline and Logan only implemented changes to the same automated task. However, this does not inform the nature of automatic skills when only surrounding context changes occur to the same task. Automatic skills are often required in differing contexts where the same stimuli and process is required.

Speelman and colleagues (e.g., Johnson, 2005; Speelman & Kirsner, 1993; Speelman et al., 2011; Speelman & Parkinson, 2012) utilised a two-step, or two part, task design in a series of experiments to investigate whether 'old' skills continue to improve under contextual

changes to the overall task. The two-part task design was implemented in the experiments reported here to facilitate the investigation of an automatic skill without directly influencing the automatic task. That is, there was a primary task (part one, e.g., counting asterisks) and a secondary task (part two, e.g., determining whether a number of asterisks were odd or even). By maintaining the automatic component task throughout the experiment and only implementing changes to the secondary task, the stimulus conditions and processing of the primary task remained the same, and so no direct changes were made to the automatic task components. On the basis of the ACT and instance theories it could be predicted that performance of 'old' skills (tasks that may be considered automated) should remain the same and demonstrate complete transfer when 'new' skills are added. However, Speelman and colleagues found that the addition of 'new' distractor items, or any change to part two of the same task in transfer, resulted in a disruption in performance. Thus, transfer performance was not just an extrapolation of training performance, and the disruption observed during initial transfer trials appears to falsify the predictions of the most prominent skill acquisition and automaticity theories. However, Speelman and colleagues design may have altered the complexity or processing requirements with the addition of the 'new' items. The experiments reported in this thesis utilised a combination of Lassaline and Logan's numerosity design and a modification of Speelman's two-step design so that context changes could be manipulated without changing the complexity or task requirements.

The present series of investigations aimed to provide data where theories are silent on the relationship between automaticity and skill transfer. Specifically, the experiments were designed to examine whether automaticity disrupts or enhances transfer performance. The research examined the relationship between automaticity, rate of skill acquisition, skill transfer and task disruption, and working memory capacity in order to determine whether any of these factors are successful predictors of skill transfer. The specific aims of this thesis

were, firstly, to clarify how performance of a task that remains unchanged during the duration of the experiment is affected by a change in surrounding context and, secondly, to investigate individual differences to determine whether transfer performance is inhibited or facilitated by the development of automaticity. This thesis has a particular emphasis on individual differences in automaticity and skill transfer, and thus individual participant data were explored in each of the aforementioned areas to determine the pervasiveness of trends observed in the group data.

Clarifying whether performance of a previously learned (automated) task is maintained when context changes occur will provide insight into whether automaticity is required for successful further learning, and will, therefore, inform the best learning practice for education and training practices. The potential benefits of such a study extend to the empirical and theoretical literature as well as to educational and remedial or therapeutic practices. With regard to the empirical literature, understanding how automaticity is related to skill transfer will assist with interpreting skill transfer performance and will facilitate better performance predictions based on individual training performance. Theoretical accounts of skill acquisition have also largely overlooked how automaticity and skill transfer are related despite empirical evidence that suggests skill transfer may not match theoretical predictions.

The results of the studies reported in this thesis are also important for therapeutic practices. As will be discussed in Chapter 3, analysis of the pervasiveness of the results has a profound impact upon interpretation of results and subsequent implementation of programs and interventions. Speelman and McGann (2013) found that the word superiority effect was not found in almost half of their 500 participants. Thus, group statistics need to be interpreted with caution. Formulating therapeutic and remedial programs based only on group results may have a substantial impact upon those individuals who do not necessarily conform to group performance patterns. Furthermore, exploring individual predictors of performance

may identify whether skill transfer is likely to occur in a group of individuals. In education there is long standing debate on traditional learning methods (e.g., rote learning) versus contemporary inquiry based methods; however there has been a paucity of empirical evidence that supports either. Whilst the results of this thesis will not provide clarity of this debate, it will however assist in identifying the likelihood of an educational program's success based on individual performance characteristics. Identifying performance characteristics that support the development of automaticity and successful skill transfer will enable insight into assessable student learning features that may indicate if and when more complex tasks can be attempted.

To achieve these aims, the thesis reviews previous research pertaining to automaticity (Chapter 2), skill acquisition (Chapter 3), and skill transfer (Chapter 4). These chapters provide the relevant background literature to the studies reported in Chapter 5. Within Chapter 5, each experimental sub-section introduces a rationale for the study, describes the methodology, presents the results, and concludes with a discussion.

The main discussion (Chapter 6) begins with a detailed synopsis of the research within the context of the research questions and previous literature. The theoretical and empirical implications of the studies are discussed, followed by the limitations of the overall study. This thesis concludes with a discussion of future research directions and an overall summary.

# Chapter 2: Automaticity

This chapter describes the major principles of automaticity. The central focus of this thesis is the relationship between automaticity and transfer, thus the chapter highlights the key theoretical and descriptive contributions of automaticity in order to determine whether automaticity is fixed or flexible in allocation and control—in other words to enquire how transferrable automated skills can be. Issues surrounding a central definition and alternative explanations of a well-replicated demonstration of automaticity, the Stroop Effect, are also reviewed.

Automaticity, the instant "popping into mind of familiar knowledge when we need it" (Logan, 1991, p. 347), is a well-known phenomenon. A response or habit that is considered automatic does not necessarily need to occupy the details of the task at a conscious level in order to carry out the task (Logan, 1988). Automatic tasks can be performed quickly, effortlessly, and relatively autonomously (Chiappe, Siegel, & Hasher, 2000; Hasher & Zacks, 1979; Jonides & Irwin, 1981; Logan, 1985; Schneider & Shiffrin, 1977). There are many human behaviours that can proceed automatically, such as driving a car or recalling times tables. However, whilst being able to perform activities quickly and effortlessly with little thought may appear to be of benefit, it is not without cost.

Automaticity can also be considered a hazardous state of mind. When we perform a task, automated performance can lead to errors, such as adding two sugars to your coffee instead of one when you are trying to cut down your sugar intake. Sometimes automaticity can even lead to catastrophes (Reason & Mycielska, 1982). Automaticity has been considered by expertise researchers to result in habituation and routine expertise (Hatano & Inagaki, 1986). The reflexive nature of automaticity when performing a well-learned task is of concern when adaptive and flexible skills are required. For example, in situations that require

flexible automatic skills where expertise is transferrable, rigid automatic skills can be problematic as they can become bound to the context of which they were acquired (Hatano & Inagaki, 1986). Conversely, Bilalić, McLeod, and Gobet (2008a) suggest that expertise may lead to either flexibility or inflexibility, dependent on the level of expertise. That is, factors such as knowledge or experience may mediate the ability to switch between flexible and rigid skills where necessary.

Automaticity is an important phenomenon in skill acquisition that has been described throughout the literature in cognition, motor skill learning, and education. Automaticity is heavily relied upon in mainstream education and training, and is considered imperative to skill learning. Skilled performance is suggested to require the acquisition of a number of automatic processes and procedures (Chase & Simon, 1973; Logan, 1985). Dating back to 1899, William and Harter claimed that lower level processes need to be automatised before the acquisition of higher level components can be attempted. Non-automatic skills are suggested to require greater attentional demands and inhibit the ability to attend to higher order tasks due to attentional requirements. Automaticity of base level skills frees up attentional capacity to deal with the attentional demands of more difficult tasks (William & Harter, 1899). Thus, automaticity may be considered an essential component of skill acquisition and some have argued that automaticity may be a mediating factor in skill acquisition (e.g., William & Harter, 1899; LaBerge & Samuels, 1974). For example, reading is considered a learned automatic skill. There are a number of basic level processes and procedures that need to be automated in order to obtain the ability to fluently read and process meaning from text. Initially, readers may need to identify words and letters automatically. This requires more than just an understanding of the relationship between letters and sounds. Knowledge of high frequency words and font variation also needs to be automatically processed and readily retrieved. By automatising sub-skills, more complex

actions can be attempted, such as comprehension and critical thinking, which result in skilled and fluent reading. Therefore, automaticity may be considered essential in learning to facilitate higher order cognitive thinking and task execution.

Previous research has highlighted the importance of automaticity for skilled learning; however the association of automaticity with rigid versus flexible skills questions the way in which automaticity contributes to higher order learning. The current study is concerned with the usefulness of automaticity in skill learning; specifically how automaticity affects the transferability of skills. Before addressing the role of automaticity in skill transfer, the defining features and applications of automated performance are reviewed. The next section presents the features and theoretical accounts of automaticity in skill learning, and highlights some of the ambiguities and underpinning issues of a collective definition.

## Defining Automaticity

Typically, automaticity describes skilled, habitual, and stereotyped performance (Moors & De Houwer, 2007). This implies that automatic skills differ from non-automatic skills in both performance and processing. For example, automatic processing is suggested to differ in speed (Logan, 1988; Neely, 1977; Posner & Snyder, 1975), effort (Logan, 1978; Logan & Zbrodoff, 1979; Schneider & Shiffrin, 1977), autonomy (Logan, 1980; Posner & Snyder, 1975; Shiffrin & Schneider, 1977; Zbrodoff & Logan, 1986), generalisability (Logan, 1988; McLeod, McLaughlin & Nimmo-Smith, 1985; Naveh-Benjamin & Jonides, 1984), and awareness (Carr, McCauley, Sperber, & Parmelee, 1982; Marcel, 1983) compared to non-automatic processes. The following section considers the research evidence relating to the aforementioned properties (the role of practice and speed as identifying factors of automaticity are discussed in Chapter 3, in the subsection The Power Law of Learning). Many of the properties co-occur or overlap in terminology and definition and so they are

discussed under three broad headings: ballistic and autonomous processing, awareness and attention, and effort.

###### The ballistic and autonomous nature of automaticity.

Automatic behaviour is commonly associated with primitive biological reflexes, such as an eye blink in response to a puff of air, the patellar reflex, or the Babinski reflex (Besner, Stolz, & Boutilier, 1997). An automatic process is described as the uncontrollable response to a given stimulus, which prevails in all contexts or situations in the absence of conscious awareness or effort (Hasher & Zacks, 1979; Posner, 1978). Schneider and Shiffrin (1977, p. 2) state, "once learned, an automatic process is difficult to suppress, to modify, or to ignore". This description implies automaticity is reflexive in nature where, once a stimulus signifies for the task to begin, suppression of the response is difficult.

Automaticity has been described by Bargh (1990) as reflexive, compulsive, and ballistic in nature. Thus, an automatic task may be considered to run until completion once started, without conscious monitoring. Ballistic processing refers to a reduction of conscious processing, which is the monitoring of intentional goal setting and intentional evaluation of outputs (Tzelgov, 1999). A process is considered automatic if it has acquired the ability to run without monitoring (Tzelgov, 1999). Therefore, a task may be carried out either autonomously or intentionally. Zbrodoff and Logan (1986) suggest that the concept of autonomy is closely linked to automaticity. Both the terminology of ballistic processing and autonomy suggests that automatic behaviour is difficult to control. Thus, automaticity may be defined as uncontrollable. In contrast, Logan (1985) suggests that automatic behaviour may be highly controllable, implying that automaticity differs in function to ballistic processing or autonomy.

Logan (1982) investigated the controllability of response inhibition using the stop-signal paradigm with experienced typists. In this experiment skilled typists were asked to type single words or sentences, and upon receiving a stop signal (either a tone or a visual signal) participants were instructed to stop typing as quickly as they could. Thus, the stop signal informs the participant to inhibit their current response. The experiment set out to investigate whether single letters or whole words are processed ballistically. Under the ballistic processing theory, automatic skills, such as skilled typing, would be difficult to inhibit due to an inability to consciously monitor or control an automated stimulus response. Typing is considered a typical example of an automatic process, and is often used to demonstrate the capability of dual processing of typing and other tasks such as answering a telephone. However, what Logan found was that expert typists were able to successfully and quickly inhibit their responses by interrupting typing mid-word, after only one or two keystrokes upon hearing the stop signal. Logan's results indicate that typing was not ballistic at the word level. Moreover, additional analyses revealed that the number of words typed per minute was also not related to stop-signal RT, further suggesting that skilled ability was unaffected by the stop signal (Logan, 1982).

Logan's (1982) results have been criticised as being limited in interpretation for two reasons. Firstly, Cohen and Poldrack (2008) argue that although the typists were considered experts in their field, and therefore considered highly automatic at typing, these typists may also be considerably skilled, and even automatic, at stopping due to sudden interruptions. Secondly, as only expert typists were utilised in Logan's study it is unclear whether the expert's stop-signal RT was faster or slower due to the automaticity of the typing skill.

In support of Logan's (1982) findings of the controllability of automaticity, Cohen and Poldrack (20008) also found evidence that automaticity may not be associated with a loss of control or development of ballistic movements. Using a stop signal paradigm with a

different task, Cohen and Poldrack investigated whether the degree of automaticity affects response inhibition on a serial reaction time (SRT) test. To determine the degree of automaticity, participants performed a concurrent secondary letter counting task. With practice, performance on the SRT task decreased, and performance cost decreased on the dual task manipulation, indicating that automaticity was achieved. Participants were then grouped as either fully automatic, or less automatic according to SRT and dual task performance. Cohen and Poldrack found the level of automaticity was not associated with a loss of control or development of ballistic movements. Specifically, it was found that participants who were identified as fully automatic or less automatic did not differ in response inhibition on the SRT task. They concluded that exerting motor control over automatised behaviour is possible in some tasks, such as the serial RT task. Given Cohen and Poldrack, and Logan's findings, automaticity appears to be unrelated to the ability to control behaviour. However, control over attention may be harder to suppress.

**Awareness and attention as mediators of automaticity.**

LaBerge and Samuels (1974) introduced the idea of attentional limitations, whereby attentional capacity limits the execution of higher-level skills if lower-level skills are not automatised. LaBerge and Samuels suggest attentional demands are 'freed up' by automatising lower-level processes so that higher-level procedures can be attended to. Automaticity is considered a way around resource limitations of central processing capacity, as automatic processing is not vulnerable to processing limitations (e.g., LaBerge & Samuels, 1974; Logan, 1978; Posner & Snyder, 1975; Shiffrin & Schneider, 1977).

The modal view of automatic processing suggests that automaticity is processing without attention (Hasher & Zacks, 1979; Logan, 1980; Logan & Zbrodoff, 1979; Posner & Snyder, 1975; Shiffrin & Schneider, 1977). The modal view of automaticity is commonly viewed as a single capacity view of attention that associates automaticity with limited

processing resources (Kahneman, 1973). On the other hand, Kahneman's (1973) single capacity theory of attention suggests that attentional capacity strengthens performance, so that the rate of processing is dependent on the amount of capacity allocated to a process. It is suggested that automatic processes are associated with faster processing and less attentional demands. Thus, the modal view posits a gradual withdrawal of attention where automaticity does not require capacity and cannot be controlled by allocating resources. Theoretical positions concerning automaticity and involvement of attention under the modal view include the controlled processing theory (Shiffrin & Schneider, 1977), conscious strategies theory (Posner & Snyder, 1975), the resource account (Ackerman, 1988; Logan, 1985), and the effortful memory theory (Hasher & Zacks, 1979).

Some researchers argue against attentional capacity limits (i.e., Spelke, Hirst, & Neisser, 1976) and a reduction of capacity demands (i.e., Kolers, 1975) as defining features of automaticity. Nonetheless, there is a qualitative difference in performance associated with practice, where task execution before practice is usually conscious, slow and error prone, and then after practice may be rapid, accurate and require little attention (Schneider & Fisk, 1982). Automaticity has been implicated in the differentiating between involuntary and directed attention. Some have interpreted this shift in attentional requirements as a change in directed attention. Involuntary attention is suggested to be automatic; whereas directed attention may be required for non-automatic tasks where deliberate, effortful task execution is required (Kaplan & Berman, 2010). Kaplan and Berman (2010) suggest that involuntary attention is considered autonomous, stimulus driven, and less goal directed and controlled than directed attention, and is therefore more automatic than directed attention. Yet, automaticity cannot be simply defined as not requiring attention, which implies an all-or-nothing process of automaticity or dual mode of automaticity. Automaticity is suggested to vary in its requirement of attention and does not exist in an all-or-nothing manner (Moors &

De Houwer, 2006). Kaplan and Berman contend "involuntary attention is more automatic than directed attention, as it is more autonomous and stimulus-driven and less goal-directed and controlled than is directed attention" (2010, p. 46).

**Effort.**

Shiffrin and Schneider (1977) highlight two mechanisms of attention allocation. Firstly, there is voluntary allocation of attention and secondly, automatic activation of attention resulting from a prior automatic relevance detection (Moors & De Houwer, 2006). Automatic processes are suggested to use minimal attentional capacity (Hasher & Zacks, 1979; Logan, 1979, 1980; Posner & Snyder, 1975). Attention can be directed to processes that are automatic; however attention is not necessary to complete the task (LaBerge & Samuels, 1974; Posner & Rogers, 1978). A change in attentional requirements of automated skills can also been interpreted as a shift in the obligation or effort of encoding and processing (Moors & De Houwer, 2006). A process is defined as effortless when it consumes little or no processing resources or attention capacity. Due to its minimal attentional requirements, automatic processing may be considered effortless or efficient, and may run in parallel with other processes with no interference. Effortful processes require substantial attentional resources, do not allow concurrent task execution, and must be processed serially. Evidence of automaticity being effortless lies within everyday examples in tasks where we seemingly operate on 'automatic pilot' (e.g., reading, driving etc.) where little effort is needed to engage in the task. Competing interference from concurrent tasks is suggested to be demonstrative of the effort required in completing a non-automatic task, thus the greater the impact of competing information on task performance the less automatic the task may be. That is, automatic processing does not inhibit processing of other information (Logan, 1997).

Research utilising the dual task paradigm highlights the impact of interference on effortless skills. Posner and Boies (1971) utilised the dual task paradigm to demonstrate automatic

encoding of letters. In their study two letters were presented successively and participants were required to determine whether the letters were the same or different. A secondary task occurred on half of the trials. The secondary task involved a simple response to white noise probe tones, which occurred before or after the first letter, or after the second letter. Posner and Boies found that there was no difference in response times with or without the secondary task. Posner and Boies concluded that letter encoding is automatic, and does not require effortful attention, thus letter encoding does not require the involvement of a limited capacity attentional mechanism, nor is it subject to interference. Further to this, Posner and Klein (1973) also found that even when the first letter is only exposed for 50 ms the encoding process required no additional processing capacity, indicating that letter recognition is effortless and thus automatic.

Physiological changes associated with elevated levels of arousal have been linked to stress or task difficulty. According to Kahneman (1973, p. 10) "variations of physiological arousal accompany variations of effort", thus a more difficult task (or one that is not yet automated) will require and result in increased arousal, indicating an increase in effort. Further to this, Chein and Schneider (2005) highlight that changes in brain activation patterns coincide with performance changes, from needing more directed attention to less attention and becoming more involuntary in execution. Specifically, Chein and Schneider found that the brain region responsible for episodic retrieval was more active for new unpractised stimuli compared to known practiced items. This idea is referred to as the effort-retrieval theory, which posits that less effort is needed to recall items that have a strong memory trace (Stanners, Meunier, & Headley, 1969; Sternberg, 1969). That is, the time to retrieve information increases as the strength of information decreases, so reaction time in this instance equates to effort. However, caution is needed when concluding that arousal level

relates to level of effort, as there are a multitude of factors that could lead to an increase in arousal other than just increased effort.

## Problems with the Property List Approach

The attempts to define automaticity described above could be considered as property list approaches. Rawson (2004) identified a sample of studies from the text processing literature that describe automaticity as a list of properties. Each set of properties describing the automaticity of text processing is different, with some explicitly identifying properties that others reject. Rawson's findings highlight the inconsistency in defining automatic skills. Logan and Klapp (1991, p. 179) support this interpretation, further suggesting "approaches that define automaticity in terms of manifest properties, such as speed, effortless, and autonomy (property-list approaches), are stipulative or descriptive but not predictive". The property list approach, although useful in distinguishing automatic and controlled processes, raises questions about the characteristics necessary for processing to be considered automatic.

Thus far it has been identified that automatic processing differs from controlled processing in the allocation of attention, control and effort. Characteristics of automaticity may explain how practice leads to an accumulation of knowledge resulting in reduced attentional demands; however, the mechanism by which this occurs has not been identified. Furthermore, automaticity has thus far been conceptualised in a fixed all-or-none manner that is uncontrollable by way of attention and effort. The following section provides an account of the dual processing theory in order to distinguish the features of automaticity and controlled processes and identify the mechanism under which automatic processes are thought to occur.

## Controlled Versus Automatic Processing

In this section I describe two approaches: Schneider and Shiffrin's (1977) dual processing theory and Hasher and Zacks' (1979, 1984) effortful processing theory to contrast the defining features of controlled processing versus automatic processing.

### Dual processing theory.

Schneider and Shiffrin (1977) contrast the implicit, unconscious nature of automaticity with the explicit, conscious nature of controlled processing in their dual processing theory. Schneider and Shiffrin explain that controlled and deliberate processes are used for difficult and unfamiliar tasks. Through practice under appropriate conditions, performance can shift from difficult to effortless and automatic. Such processes operate in parallel, require few cognitive resources, do not rely on attention, and are difficult to modify (Speelman & Mayberry, 1998).

According to Schneider and Shiffrin (1977) an integral aspect of learning and automaticity involves memory sequencing. Memory is conceived to be a large and permanent collection of nodes that become complexly and increasingly inter-associated and inter-related through learning (Schneider & Shiffrin, 1977). Nodes that are active reflect short-term memory, whereas nodes that are passive reflect long-term memory. Active nodes are a temporary state in which manipulation or control of information takes place in order to facilitate memory transfer from short-term to long-term nodes. Temporary sequences of nodes are activated through control and attention. Thus, controlled processing requires a deliberate allocation of attention to activate a novel sequence of memory nodes. Only one sequence at a time may be controlled and attended to in short-term memory without interference, due to a limited capacity. Inactive and passive nodes reflect long-term memory and permanently stored information. A series of sequences can be retrieved automatically

without attention or deliberate control. Thus, in contrast to controlled processing, automatic processes can be triggered by internal or external stimulus conditions to activate a sequence of memory nodes without attention and with minimal resources. Automatic processes are therefore defined under the controlled processing theory as the activation of a particular sequence of nodes that almost always become active without attention or deliberate control (Schneider & Shiffrin, 1977). This absence of control and attention is facilitated through a considerable amount of training and practice (Schneider & Shiffrin, 1977).

In order to investigate the contrast between automatic and controlled processing Schneider and Shiffrin (1977) devised a search task whereby participants would search through sets of items (letters and numbers) for pre-defined target items. Schneider and Shiffrin manipulated the nature of the target stimuli. In the consistent mapping (CM) conditions a set of items was consistently designated as target stimuli throughout the experiment. Because the same stimuli were repeatedly attended to, there was scope for automatic processes to develop. In the varied mapping (VM) condition a stimulus that was assigned to a given response on one trial (e.g., target) was assigned a different response (e.g., distractor) on the next trial. In VM, the prior and current associations were incompatible, thereby precluding the development of an automatic attention response. Instead, controlled processing was required, which is considered voluntary, serial, and requires attention.

Automatic processing is fast and parallel, requiring little attention or awareness, and develops with extended practice when targets are consistently mapped to responses. Information processing is then faster and more efficient, with higher accuracy, and is unaffected by workload. However, in the real world complex task decisions are made in inconsistent or varied conditions (Kramer, Strayer, & Buckley, 1991). Very rarely in everyday life would it be possible to perform under the same conditions consistently. For example, when learning to drive a car we experience varied terrains and weather conditions,

and have to make quick decisions to avoid traffic hazards. However, over a considerable amount of practice, there are certain driving procedures that become automatic, such as changing gears and indicating to turn.

According to Schneider and Shiffrin's (1977) dual processing theory controlled processes are serial, use resources, require attention, and are flexible—that is they can adapt to task changes and strategy use can vary. Conversely, automatic processes are difficult to modify. The dual processing theory views attentional requirements as either automatic or non-automatic, both of which have a fixed set of requirements, with no allowance for crossover in attentional resources, and is termed the 'all or none' view of cognitive processing (Moors & De Houwer, 2006). This 'all or none' view has been questioned and challenged by many studies (e.g., Bargh, 1992; Kramer et al., 1991; Logan, 1985, 1988, 1989) because of the difficulty in identifying a task that only requires controlled or automatic processes. Many tasks may have components that require attention and control whilst other components are automatic (Bargh, 1992).

Others, such as Carlson (2002) and Hommel (2000), suggest that although automaticity is often referred to as occurring without intention, automaticity may be better understood in terms of goal directed information processes or intentions. That is, unconscious or automatic processing inadvertently involves goal directed processes (Bargh & Chartrand, 1999). Under appropriate circumstances basic procedures may operate automatically (obligatory or ballistic manner) yet an individual must still control the process of what to do. That is, each step of mental activity may need to be chosen out of several alternative procedures (Carlson, 1997). Goal structures determine moment-to-moment activity and are generated from an individual's learning history or reasoning and problem solving. According to Carlson (1997) the goals that control mental activity are part of the content of conscious intentions that may represent how to carry out individual steps of mental activity, however the details of these procedures

will not be conscious. Conscious intentions also control when and where to perform basic processes.

Further to this, although Schneider and Shiffrin's (1977) theory considers imperative features between automatic and controlled processes and the circumstances under which each can apply, Speelman and Mayberry (1998) point out that an underlying mechanism to explain this transition from controlled to automatic processing is lacking. A number of theories have been presented that address some mechanisms for the acquisition of automaticity, which largely fall into two categories: the procedural account and the memory account. The predominant examples of these two categories are the ACT and instance theories, which are addressed in Chapter 3.

**Effortful processing.**

In contrast to Schneider and Shiffrin's (1977) dual processing account is a theory presented by Hasher and Zacks (1979; 1984) which considers automaticity at no stage to be controlled, and identifies automaticity to be innate and built-in to the human-information processing system. Hasher and Zacks posit that controlled processes require effort, and so limit one's ability to engage simultaneously in other effortful processes. Effortful processing imposes the idea that memory efficiency increases with practice, and that effortful strategies can be implemented through the use of imagery and mnemonic devices to increase learning speed. Encoding is suggested to fall along a continuum from effortful processing to automatic processing. This is similar to the distinction between automatic and controlled processes as described by Schneider and Shiffrin. Both theories suggest that automatic processes require minimal attentional resources, can be initiated without awareness or intent, and are difficult to inhibit. However, Hasher and Zacks suggest that certain automatic processes are innate and that we are programed to be susceptible to becoming automatic on some tasks.

Our nervous system is 'hard-wired' to process certain kinds of information, thus, we have a preparedness to learn. For example, we are pre-programed to encode spatial location, event frequency, and temporal order (Hasher & Zacks, 1979). The conceptualisation of innate automatic processing is similar to Reber's (1992) assumption of implicit learning capabilities. Reber suggests that primitive and basic encoding shows little variation across age and intelligence, which typically has considerable impact on cognitive processing.

The term 'hard-wired' has been criticised over its robustness. Neuroplasticity research suggests that very few psychological capacities are genuinely hard-wired, and that environmental experiences are capable of modifying such 'in-built' responses (e.g., Huttenlocher, 2009; Shermer, 2011). Research has questioned Hasher and Zacks' (1979) view of innate automatic readiness; however the general consensus is that automatic processes and consciously controlled processes are fundamentally different.

**Challenges to the current definitions of the modal account of automaticity.**

Interestingly, others (e.g., Kolers, 1975; Spelke et al., 1976) argue against the two predominant characteristics of automaticity: attentional limits and a reduction of capacity demands. For example, Kolers (1975) suggests that automaticity is not just unskilled processing executed faster and requiring less attention, instead automatised skill may be composed differently to controlled processing. That is, automatic processing may be more selective and involve directed analysis of task components. There is also evidence from Spelke et al. (1976) that questions the role of attention as a defining property of the transition from automatic to controlled processing. In Spelke et al.'s study two subjects practiced reading short stories while dictating lists of words. Spelke et al. found that the two participants were able to divide their attention where necessary. Thus participants were able to establish automaticity in both tasks, thereby supporting Posner and Snyder's (1975) suggestion of interference as a mediator of controlled versus automatic processing. However,

the participants were able to divide their attentions accordingly based on the task demands and demonstrate improvement in comprehension, which would appear to contradict the underpinning principles of the modal account of automaticity, which stipulates a reduction of attention and an all-or-none view of capacity demands. Thus, participants did not necessarily act on 'automatic' pilot, and instead demonstrated an increased ability to divide attention. Spelke et al. concluded that it may never be possible to define general limits on cognitive capacity, and attentional skills are no exception.

The modal account of automaticity (e.g., LaBerge & Samuels, 1974; Posner & Snyder, 1975; Shiffrin & Schneider, 1977) has been challenged on several grounds. Resource theories argue that automaticity is largely governed by a counterbalance of available resources resulting in either controlled processes or automatic processes. However, multiple resource theorists (e.g., Navon & Gopher, 1979) have argued that more than one resource limits performance, making it unclear which resources an automatic process uses fewer of. The multiple resource theory suggests that the resources a task requires may change with practice (Ackerman, 1988). Thus, automatic processes may use more of some resources than non-automatic processes, which violate the fundamental assumption that automatic processing is resource free.

Another set of theories view automaticity as a memory phenomenon (e.g., Anderson, 1982; Logan, 1988; Newell & Rosenbloom, 1981). These theories consider novice performance, or non-automatic performance, to be based on a general problem-solving algorithm, whereas automatic performance is based on a single-step retrieval of past solutions from memory. Thus, automaticity is construed as a memory phenomenon; therefore, it could be explained using the same theoretical and empirical principles of memory. Under this view, automaticity shares properties of well-practiced memory retrieval, which is fast and effortless

(Logan, 1991, 1992). If this is the case, automatic processing is not processing without attention, but rather a different way of attending to information (Logan, 1985).

## The Stroop Effect as a Demonstration of Automaticity

Automaticity has been demonstrated in a range of experimental tasks, such as alphabet arithmetic, lexical decision making, relative judgement, categorisation, dual task scenarios, visual numerosity, and most predominantly the Stroop paradigm (Hélie, Waldschmidt, & Ashby, 2010; Lassaline & Logan, 1993; Loft, Humphreys, & Neal, 2004; Logan & Klapp, 1991; Stroop, 1935). The Stroop task illustrates how an automatic skill, such as reading, is difficult to suppress once triggered, resulting in what is referred to as the Stroop Effect. Furthermore, the Stroop effect demonstrates the role of interference in defining an automatic skill (MacLeod, 1991). Participants are presented with words referring to colours (e.g., red, blue, green), which are printed with different ink colours. They are asked to name the colour of ink (red, blue, green, brown, and purple) of either congruent (i.e., 'red' printed in red ink) or incongruent ('red' printed in green ink) words. Stroop (1935) found that subjects took, on average, 47 seconds longer to name incongruent words compared to the congruent words, this is referred to as semantic interference. He concluded that words evoke a single reading response and this response is widely practiced and considered highly automatic and demonstrates the durability of automatic skill establishment that is difficult to suppress. The Stroop effect is a classic example of the robustness of automatic skills, and it has been replicated numerous times (e.g., see McLeod, 1991 for a review). The effect occurs regardless of instruction to ignore incongruent words, this has led some researchers to conclude that reading is an automatic process, which is difficult to suppress or modify. That is, subjects access the meaning of words automatically with little effort or consciousness, whereas colour naming requires more effort than reading, creating interference in the Stroop effect (Tzelgov, Henik, & Berger, 1992). However, more recent research has criticised the

robustness of the effect to be attributed to testing conditions and priming effects (e.g., Besner et al., 1997; Lindsay & Jacoby, 1994).

The imbalance of attentional resources in the Stroop task is attributed to our extensive history of word reading practice compared to ink naming (MacLeod, 1991). A more automatic process can interfere with a less automatic process, but not vice versa, due to the obligatory characteristic of automaticity (MacLeod, 1991). However, word reading is not attained automatically (Grabe, 2010). Reading is a skill that with practice transitions from a controlled and heavily attended task to a reflexive automatic process durable beyond the context in which the skills were developed (Rawson, 2010).

MacLeod (1991) suggests that practice affects the impact of interference. The more automatic a process becomes, the more it is capable of causing interference with a less automatic process. The reverse Stroop effect supports this conclusion. The reverse Stroop effect is where the sensory colours interfere with identifying colour words. For example, when an incongruent coloured word (i.e., the word "red" written in green ink) is presented with four coloured squares (i.e., red, green, yellow, and blue), and participants are asked to match the written colour (i.e., red) with the matching coloured square, response times are delayed; incongruently- coloured words significantly interfere with pointing to the appropriate square (Durgin, 2000). When a normally more automatic process is altered by an experimental manipulation, the normally less automatic process may become more automatic. In such instances the Stroop interference reverses (Macleod, 1991).

The literature describes three possible explanations of the Stroop effect involving interference of competing information. First, the typical Stroop effect is suggested to arise from output interferences occurring due to the competition between vocal responses to the word and ink colour (Keele, 1973). Second, the direction of interference depends on the time

relations involved—words are read faster than it takes to name a colour—due to differences in processing. Thus, greater interference results from the time taken to name the colour versus naming the word. Third, words facilitate vocal output to colours with which they share a common name (Hintzman, Block, & Inskeep, 1972). These three factors explicate that incongruence of competing information results in increased reaction time for colour naming compared to word naming.

Thus far, it has been highlighted through the Stroop task paradigm that automaticity is related to attention and allocation of resources, however, the role of practice in reducing interference of an automatic skill may be equally important. Although theoretical explanations can attribute the Stroop findings to one or more characteristics that have been highlighted in the automaticity research, the phenomenon of the Stroop effect is not without criticism. Some researchers criticise interpretations that the Stroop effect demonstrates automaticity. Others criticise the replicability of the effect, and some highlight the role of variables, such as experimental context, as mediators of the Stroop effect. Details of these criticisms are discussed below.

Besner et al. (1997) suggests that priming to read printed words may be responsible for the Stroop effect. As participants are typically presented with congruent words and colours (e.g., 'red' written in red ink) in the initial phase of testing, participants could have just read the word and been praised for performing a successful trial. Given this experimental design there is no way of determining whether or not the ink colour was being reported or simply being read. Thus, it is plausible that participants were being primed to read the word instead of reporting the ink colour, which in turn could have affected the next trial of incongruent words and ink colours. Besner et al. investigated evidence for the Stroop effect when manipulating experimental design elements. They found that interference in the Stroop task can be reduced (experiment one) and even eliminated (experiment two) through the use of

mental sets. For example, Besner et al. found that when limiting the ink colour to only a single letter instead of the whole word, the Stroop effect was eliminated, indicating that words are not necessarily read automatically. This specifically rejects the notion that, if the Stroop effect is an example of automaticity, an automatic process cannot be suppressed or refrained from being fired or initiated. Thus, the literal context may be more important at mediating the effect rather than the explicit instructions to name the colour ink and not the word. The context presented in the original Stroop task, as well as in many other replications, primes participants to read by setting up mental structures and the pathways that connect them. Thus a 'mental set' is primed with the context presented. In terms of the general explanation of automaticity, Besner et al. concludes that by classifying some skills as automatic we may fail to recognise and identify the underlying processes.

The magnitude of the Stroop effect appears to be affected by the number of congruent trials in a list, such that the Stroop effect is larger when the proportion of congruent trials is higher than when the proportion of congruent trials is lower. So participants are primed into word reading rather than colour naming. This is referred to as the proportion by congruency interaction (e.g., Lindsay & Jacoby, 1994; Logan & Zbrodoff, 1979). These findings alone question whether automaticity is as ballistic and durable as the congruent definition suggests, or whether experimental conditions used in experiments, such as the Stroop task, are an ineffective measure or demonstration of automaticity and instead demonstrate adaptation to experimental contexts. This questions whether participants actively moderate strategies that result in automatic-like performance, or whether individuals implicitly react and assimilate to environmental changes. This question concerns one aspect of the definition of automaticity— the role of awareness.

Blais, Harris, Guerrero, and Bunge (2012) investigated the awareness of the proportion of congruent trials as necessary for the proportion of congruency interaction. They

investigated the relative contribution of self-regulated conscious (deliberate) strategies versus implicit adaptations to knowledge of the experimental design on performance of the Stroop task. Blais et al. suggest that if participants informed of the composition of an upcoming block then they might be able to implement an overt strategy, best suited to the task. However, Blais et al.'s group results demonstrated no significant difference whether participants were aware that there were more congruent trials than the number of incongruent trials within the block. This suggests that awareness of the proportion of congruent trials plays little role in the proportion by congruency interaction. Blais et al. suggests that this does not indicate that an individual is unable to apply an explicit strategy, but that participants may be subconsciously adapting to their environment. However, Blais et al. report that, upon inspection of the proportion by congruency interaction, the effect was larger than when there was no encouragement, indicating that automaticity may be mediated despite the absence of a significant interaction.

The aforementioned studies suggest that context plays a role in the development or execution of an automatic skill. This would seem to defy current and past statements of the characteristics of automaticity, such as obligatory encoding, stability, and control of attention and awareness. Therefore, automaticity may not be as reliable or as fixed as what has been claimed by some researchers.

Dishon-Berkovits and Algom (2000) employed the Stroop task to demonstrate how a change in contextual information can impact automaticity. Dishon-Berkovits and Algom changed the context of the Stroop task by manipulating the number of congruent and incongruent colour-word trials. Dishon-Berkovits and Algom found the Stroop effect could be manipulated due to the relationship of the distractors to the target. Specifically, in experiments one to three dimensional correlation appeared to affect selective attention. When conditions were neither a component of the stimulus or indicated information about the other

component, selective attention was good. However, when dimensional values covaried, the Stroop effect was evident. In experiments four and five, context appeared to influence selective attention. That is, picture-word stimuli affected the Stroop interference where pictures interfered with the categorisation of words. Irrelevant words did not interfere with categorisation of pictures. Dishon-Berkovits and Algom suggest that the context of the distractor item will limit attention to the target, thus informative and salient distractors produce the greatest interference. Dishon-Berkovits and Algom support the findings of others (i.e., Besner et al., 1997) who suggest the Stroop effect encompasses attentional systems rather than automatic processing and is evidence of the predictive relationship between words and colours of the Stroop design.

Similarly, Labuschagne and Besner (2015) found that attention can be mediated and thus occurrence of the Stroop effect can be manipulated. Semantic processing is said to be responsible for the fast, efficient manner of word identification in the Stroop task. Labuschagne and Besner suggest that semantic processing in the Stroop task can be eliminated by changing spatial attention. In their experiment the classic Stroop effect was replicated when the basic premise of the task was implemented. That is, when the whole word was printed and coloured in associated ink (i.e., "red" printed in 'red' ink). However, Labuschagne and Besner found that by spatially separating the letters and colouring only single letters, as opposed to the whole word printed in coloured ink, the Stroop effect was eliminated. For example, "red" may be presented as "R E D". Labuschagne and Besner's findings were commensurate with the earlier findings of Besner et al. (1997) and support the suggestion that automaticity may not be stable across varied contextual conditions if automaticity can be manipulated with minor experimental changes.

It has also been suggested that modality is a predictor of the Stroop effect. Durgin (2000) found that a reverse Stroop interference is found when a pointing task is implemented,

while nearly eliminating traditional Stroop interference. Prior experiments by Pritchatt (1968) and McClain (1983) found that the Stroop effect can be eliminated by utilising another modality for colour naming. For example, colour matching has been used, whereby coloured patches were placed on or near buttons that were to be used as responses. Pritchatt demonstrated a reduction in interference, but little reversal. McClain also reported elimination of Stroop interferences using coloured buttons. These findings contradict automaticity or strength association explanations of the Stroop effect (e.g., Cohn, Dunbar, & McClelland, 1990). Durgin instead suggests that the Stroop effect is due to response compatibility and subsequent response competition. This questions the typical interpretation of the Stroop effect.

Although the main view is that automatic performance involves fast, effortless, unconscious, autonomous, and involuntary processing developed with extensive practice (Hasher & Zacks, 1979; Logan, 1980; Posner & Snyder, 1975; Shiffrin & Schneider, 1977), contradictory evidence from Regan (1981) suggests that extensive practice may not be required for involuntary processing. Thus, terminology such as 'effortless' and 'autonomy' may not typically co-occur in automatic processing (Regan, 1981). This further suggests that automaticity may not be internally consistent in definition. Therefore, based on the reviewed evidence, the reliability and consistency of identifying and defining automaticity may be called into question.

## The Failure of Automaticity in Skilled Expertise Research

Automaticity is considered a characteristic of expertise. The expertise literature refers to automaticity as highly specific to the stimuli and conditions experienced during training, so much so that skills are highly attuned to the conditions under which automaticity was developed. The expertise literature refers to this type of expertise as 'routine expertise'

(Hatano & Inagaki, 1986). In circumstances where conditions do not change, domain-specific knowledge develops over an accumulation of experience that mostly consists of problem solving in a given domain. Thus, automaticity may be established; yet, in conditions where things do change a lot, automatic skills are unlikely to develop, and so may lead to more adaptive expertise (Hatano & Inagaki, 1986).

Increased task errors and errors in planning have been attributed to automaticity, and prior experience and stimulus familiarity in chess (e.g., Bilalić et al., 2008a, 2008b; Reingold, Charness, Pomplun, & Stampe, 2001) and medicine (Croskerry, 2003; Gordon & Franklin, 2003). For example, it is suggested that prior knowledge or domain specific knowledge interferes with problem solving when familiar problems or solutions are presented, so that a familiar, but inappropriate, solution is triggered in response. In turn, alternative solutions are prevented from being considered (Kaplan & Berman, 2010; MacGregor, Ormerod, & Chronicle, 2001). This phenomenon of cognitive bias in using an already developed problem-solving set is known as the Einstellung effect (Luchins, 1942).

Bilalić et al. (2008b) investigated the Einstellung effect amongst chess experts using eye-tracking technology. Bilalić et al. manipulated board positions so that only two positions were available; participants were required to find a checkmate in as few moves as possible. The first problem had two solutions: a familiar five-move (smothered mate) solution and a less well-known three-move solution. In the second problem, only the shorter solution was possible. All players shown the two-solution problem found the familiar smothered mate solution, and reported that although they looked for a shorter mate, they failed to find one, suggesting they were subject to the Einstellung effect. All players shown the one solution problem found the shorter, less familiar solution. The two groups of players were compared for eye movements and found that the group looking for the two-solution problem spent more time looking at the two sets of squares relevant to the smothered mate solution, despite

reports of actively looking for alternative solutions. Bilalić et al. suggest that a schema in memory is activated by the familiar pattern, and so attentional focus is directed to information relevant to the activated schema and all other contradictory information is ignored.

Additionally, failure in expert task performance has been linked to the development of attentional sets, which prevent flexible and adaptive task strategies. Attentional sets are suggested to trigger an internalised production rule, which are triggered automatically under certain situations. For example, Furley, Memmert, and Heller (2010) suggested that certain coaching practices—such as: 'if the defence responds by doing A, then you should do B; if they respond in manner C, then you should be D'—facilitated 'if-then' rule type pairings. Attention is drawn to a certain player, who subsequently completed that pass, even though it may not have been the best option available resulting in inattentional blindness (Mack & Rock, 1998). Whilst this type of instruction, or internalised production rule, serves to assist the players limited processing capacities by automatically directing their focus of attention to the next plan of action, it may also lead to errors in performance by inducing an attentional set. That is, the prioritisation of certain stimuli leads to a form of confirmation bias (Nickerson, 1998), where existing expectations direct attention and action.

Attentional sets are a vital aspect of skilled performance and are required to assist in rapid decision making; however, the automatic recall of such processing or procedures may hinder attentional flexibility, and therefore inhibit 'expecting-the-unexpected' (Pesce, Tessitore, Casella, Pirritano, & Capranica, 2007). There is evidence to suggest that control over automatic attentional processes is possessed by skilled performers in addition to reflexive automatic processes (Jacoby, Ste-Marie, & Toth, 1993).

Bilalić et al. (2008a) found that the level of expertise achieved might depict whether task execution results in flexibility or inflexibility. In chess, automaticity in skilled players facilitates parallel processing of the relational position of all the pieces on a board. Conversely, the relational position of each chess piece is processed one piece at a time by less skilled players. In a similar research design to Bilalić et al. (2008b) using the Einstellung (set) effect paradigm, chess players ranging from ordinary experts to superior experts tried to solve problems that had both a familiar but non-optimal solution and a better but less familiar one. The presence of the non-optimal solution induced the Einstellung effect even in experts, which reduced their problem-solving ability to that of player's three standard deviations lower in skill level. Experts demonstrated inflexibility of thought by prior knowledge, but the more expert they were the less prone they were to the effect. Whilst it may be argued that the players who found the right solution were significantly more skilful than players who did not and were able to utilise flexible adaptive problem solving, the evaluation of problem situations is heavily influenced by available knowledge (e.g., Gobet, 1997; Holding, 1985; Sarriluoma, 1995). Bilalić et al. (2008a, p. 92) posit "knowledge is an essential part of flexible behaviour". Thus, players that are more skilful were able to see and evaluate the optimal solution and were not bound to set solutions.

According to empirical evidence there is reason to suggest that automaticity may not be an all-or-nothing phenomenon. Errors in performance may be attributed to an over-reliance of automated processes or a failure to shift from a more automatic mode (Memmert, Unkelbach, & Ganns, 2010). That is, excessive amounts of automaticity restricting flexible and adaptable performance may lead to mistakes, slips, and lapses in skilled performance. Christensen, Sutton, and McIlwain (2016) posit that experts have the ability to shift from automatic to a more attention-based mode of control at the right time of performance. Christensen et al.'s 'mesh' theory accounts for the way that cognitive and automatic processes may co-exist with

cognitive control available for strategic elements of performance and automatic control for implementation and task execution.

## Conclusion

Characteristics of automaticity include processing that is fast (Fitts & Posner, 1976; Neely, 1977), effortless (Logan, 1978, 1979; Schneider & Shiffrin, 1977), autonomous (Logan, 1980; Posner & Synder, 1975; Zbrodoff & Logan, 1986), stereotypic (McLeod et al., 1985), outside conscious awareness (Carr, et al., 1982), and requiring a consistent environment (Logan, 1988; Schneider & Fisk, 1982). Automaticity is further characterised as a form of cognitive processing without capacity limits, and as processing that may not necessarily demand attention (Epstine & Lovitts, 1985; Logan 1988). Many definitions also include an association with primitive reflexes such as an eye blink in response to a puff of air, the patellar reflex, or the Babinski reflex (Besner, et al. 1997) suggesting that automaticity is an uncontrolled response to a stimulus in the absence of conscious awareness (Epstein & Lovitts, 1985). The ability to perform routine activities effortlessly and quickly, with little thought or conscious awareness is a phenomenon of everyday life. Without automaticity we would struggle with many of life's simple requirements, such as driving to work or understanding and calculating money, even tying shoelaces would be difficult if we had not developed the skill to automaticity. However, the evidence does not favour this extreme view. Automaticity is also considered as sensitive to minor context changes and may not be as durable as once thought. Performing on 'automatic pilot'—leaving our mind to attend to other things—may also be considered problematic (Logan, 1988).

Automaticity is suggested by the evidence of the Stroop task to be stable, predictable, and reliable, however, research further suggests that the Stroop effect does not represent a normal occurrence of automaticity, but an adaptation to a highly constrained experimental

condition. Thus far, discrepancies exist between theoretical definitions and empirical evidence of automaticity. This then leads to the need for clarity in the characteristics that not only identify automaticity but also clarity in the theories regarding mechanisms of attaining and maintaining automaticity. That is, a more cohesive understanding of how automaticity may affect task performance, and what influences ongoing automatic performance is required to provide insight into the best learning situation or learning approach.

This thesis is concerned with whether automatic skills are task dependent, thereby limiting their usability outside of the learned context. The evidence so far falters at a clear definition of automaticity and its usefulness in learning.

The following chapter (Chapter 3) considers how theories of skill acquisition explain the occurrence of automaticity, and Chapter 4 considers the transferability of learned skills.

# Chapter 3: Skill Acquisition

This chapter discusses the power law of learning in cognitive skills, a central issue throughout the thesis. Particular emphasis will be placed on individual differences as mediators of learning curve deviations and in the acquisition of automaticity. The ACT theory (Anderson, 1982, 1987) and the instance theory (Logan, 1988) will be discussed as explanations of the acquisition of automaticity and performance. The aim of this chapter is to determine whether the skill acquisition theorists consider automaticity as transferrable.

In Chapter 2 it was demonstrated that automaticity might be considered a fixed state in the end product of skill acquisition. Many examples of the robust nature of automaticity exist within the literature (i.e., the Stroop task). However, as the previous chapter highlighted, alternative explanations of the well-demonstrated phenomenon of automaticity exist. This further questions whether automaticity is fixed in nature or adaptable and flexible to change, contrary to classical demonstrations of the durability of automaticity. Specifically, this questions whether automaticity facilitates or hinders the overall learning process if automated skills need to be transferred to another learning situation. If automaticity is considered a rigid state, then learning until reaching automaticity may not be the best learning strategy where flexible and adaptable skills are required.

First, this chapter introduces the concept of skill (i.e., what is skill?), then the concept of the power law of practice will be explained, followed by an introduction to Anderson's general (1982, 1987, 1993) adaptive control of thought (ACT, ACT*, ACT-R) theory and Logan's (1988, 2002) instance theory of automatisation. This chapter highlights various ideas on the mechanisms underlying the development of automaticity, including whether skill

acquisition theorists consider automaticity fixed or flexible. Finally, there is consideration of individual differences in the acquisition of automaticity.

## What is 'Skill'?

How do we know when performing a task becomes a 'skill'? Bruner (1973) conceived the idea that skilled action is the ability to perform serially ordered acts with reduced variability to performance. Skill is also the ability to modify performance where required whilst taking into account feedback and knowledge of results (Widmer, Ziegler, Held, Luft, & Lutz, 2016). Skill acquisition then is the learning process used to acquire a new skill. This may involve prolonged learning of sub-skills and events that are then stored in memory. Skilled retrieval of productions (e.g., the ACT theory) or instances (e.g., the instance theory) leads to skilled behaviour, which may then become routinised (automatic) under some conditions (Speelman & Kirsner, 2005).

Skilled behaviour can be defined to include responses that are not innate, such as playing a musical instrument, driving a car, dancing, or even writing. It also extends beyond overt behaviour to recognising alphabetical or numerical symbols that facilitate reading. In such examples, extensive practice has led to a set of mental representations that are held in, and easily accessible from, memory so that when activated an instant typical response is available. Skilled performance is then defined as effortless, error free, and fast. Tasks, such as lexical decision (Kirsner & Speelman, 1996), geometric sequencing (Greene, Rucker, Zauss, & Harris, 1998) and arithmetic (Logan, 1988), are often used in cognitive psychology to explore the underlying cognitive mechanisms involved in skill acquisition. Changes in reaction time (RT), particularly very fast RT, are suggested to indicate skilled performance (Logan, 1988).

## Power Law of Practice

Snoddy (1926) was considered the first psychologist to highlight the continuous nature of improvement in a mirror-drawing task. Over a 60-day period, gradual improvement was noted as well as a reduction in the rate of improvement over time on a motor task. Thus, practice has been found to lead to faster and more accurate responses over time (Anderson, 1992, 1993), and the pattern of improvement is described as the ubiquitous power law of practice (Newell & Rosenbloom, 1981).

Newell and Rosenbloom (1981) investigated the nature of the mechanisms underlying improvement. They reviewed data from numerous studies comparing fits to the reported learning curves of generalised power, exponential and hyperbolic functions. Newell and Rosenbloom concluded that power functions provided a superior fit to those provided by the other functions. On this basis they theorised a single law that describes all practice data, which they referred to as *the power law of learning.* The power law of learning applies to examples such as Crossman's (1956) reports of skill acquisition at cigar rolling. When practice of a task leads to performance improvements, the improvement is usually well described by a power function (see Figure 1). As is clear in the learning curve plotted in Figure 1, early task practice usually results in rapid performance gains (i.e., decrease in RT), with a steep decrease in RT at earlier stages of practice. However, after further practice, performance gains decrease until reaching an asymptotic level in which performance does not improve any more.

A power function describes performance where:

$$RT = a + bN^{-c}$$

(1)

In equation 1, *RT* is the response time on a task, *N* is the number of practice trials, *a* is the value of response time that represents asymptotic performance (i.e., the minimum response time that a participant could achieve), and *b* represents the total amount of speed-up possible. The parameter *-c* in equation 1 is the learning rate or slope of the learning curve. The decrease in RT in skill acquisition is often graphically depicted as a 'learning curve'. Figure 2 demonstrates the parameters of a typical skill acquisition curve, where *b* represents performance on the first trial and *a* represents the asymptote.
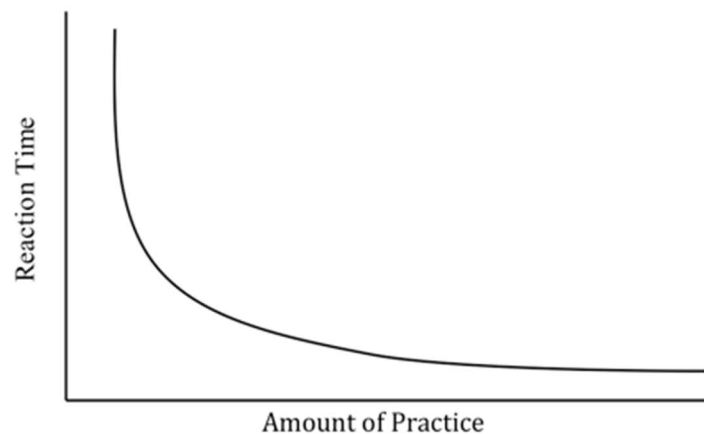


**Figure 1: A learning curve showing the typical relationship between the speed of performance of a task and the amount of practice on the task.**

The power law phenomenon has been observed in a range of tasks, such as mirror-tracing (Snoddy, 1926), solving of geometry proofs (Anderson, Greeno, Kline, & Neves, 1981), lexical decision (Kirsner & Speelman, 1996) and reading inverted text (Kolers, 1975), and is widely recognised in skilled learning and human performance (Fitts & Posner, 1967). When describing learning as a power law the nature of performance improvement as a curvilinear plateau, referred to as an asymptote, implies that there must be a limit to learning

(Tomporowski, 2003). However, the rate at which limits of learning are reached is very slow—so slow that most individuals do not reach their capacity (Fitts & Posner, 1973).
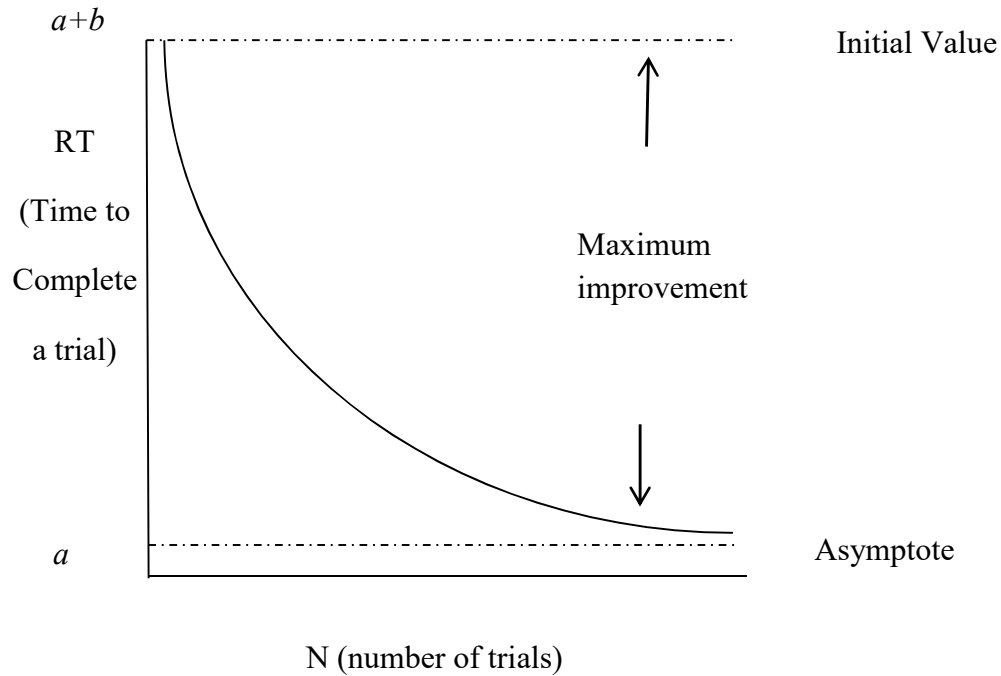


**Figure 2: Parameters of a typical skill acquisition curve.**

An often-cited example of the power law of learning is Crossman's (1956) report of the effects of practice on a hand-operated cigar rolling machine. Crossman found that when speed of performance was plotted as a function of the amount of operator experience, speed of performance increased linearly for about four years, and then performance levelled off. This levelling off in performance corresponded to the limit of the rate of work possible with the machine. Crossman concluded that the asymptotic point of the operator's learning limit might also be indicated by the levelling off in performance. As humans cannot possibly complete a task in zero seconds reductions in learning gains or improvement indicate human performance limits.

Despite the fact that power functions provide such a good description of learning curves, there have been suggestions that the power law of learning is not so law-like. Although learning curves derived from group data are more likely to be described well by power functions, individual data often reveals deviations from power functions (Haider & Frensch, 2002; Speelman & McGann, 2013). For example, Heathcote, Brown, and Andrew (2000) suggest that averaging group data provides a bias in favour of the power function. They state "practice functions from different subjects should not be averaged, not only because variation of learning rates can distort the shape of the average function, but also because an individual subject's learning may occasionally follow a function other than the usual exponential form" (Heathcote et al., 2000, p. 198). Moreover, some (e.g., Conway & Schultz, 1959) question the 'ubiquity' of the power law because of the difficulty in providing a generalised, or universal, learning function that describes a 'true' curve of learning.

It has been suggested that the generality of the power law is limited to simple tasks requiring only RT as a performance measure. Critics, such as Anderson (2001) and Murre and Chessa (2011), argue that data averaging produces an artificial power law because the averaging of many curves together necessarily produces a power function. The issue of averaging data to draw a conclusion about a phenomenon is of specific interest to the current thesis and is discussed at more length in Chapter 5. In this thesis both group and individual learning curves were considered in order to provide a thorough account of learning patterns.

## Skill Acquisition Theories

Many models of skill acquisition have been proposed, however most consider that general knowledge is the starting point for skill acquisition from which expert specialist knowledge is developed (Anderson, 1987; Crossman, 1959; Fitts, 1964; Fitts & Posner, 1967). When learning a skill, performance changes from slow and effortful to fast and

effortless. Fitts and Posner (1967) reported that this shift in performance occurs over three phases. The first stage is the *cognitive stage* where the individual draws on known resources, such as task requirements, features of the task, and strategies learned from previous tasks. In this stage performance is slow, prone to errors and requires attention. Overt verbalisation of task sequences is commonly observed. The second stage, the *associative stage,* utilises aspects of the previously learned task that are appropriate and they become strengthened through positive feedback. The feedback process involves evaluation of performance; appropriate aspects are refined and inappropriate aspects are weakened and discarded. The third stage, the *autonomous stage*, describes the shift from dependent, controlled, verbalised behaviours to faster, more efficient automatic performance.

Shiffrin and Schneider (1977) associate these phases of skill acquisition with changes in the requirement of attention from controlled to automatic processing. Controlled processing is considered slow, effortful, intentional, and requiring attention. Conversely, automatic processing is fast, efficient, error free, and requiring less attention. The contrast between the attentional requirement of controlled versus automatic processing has been reported across many higher mental processes, such as social cognition and goal oriented information processing (Bargh & Ferguson, 2000). The transition from controlled to automatic processing is consistent with Fitts and Posner's (1967) model. In the cognitive stage controlled processing is required because learning a new task places a high demand on attentional resources. Finally, the autonomous stage is where cognitive load is freed up and automatic processing is consistent. Over time the more a skill set is practiced and memory retrieval is refined the more a task can be executed with more skill than that of a novice.

Although Shiffrin and Schneider's (1977) idea of controlled versus automatic processing is widely accepted, there is a limitation in their theory in terms of how this transition occurs from controlled to automatic processing. Two theories attempt to explain

this transition: the ACT* theory (Anderson, 1992, 1983, 1987) and Logan's instance theory (1988).

**Adaptive control of thought (ACT) theory.**

A clear explanation of the mechanisms underlying skill acquisition is provided in the ACT theory (Anderson, 1987). Basic learning processes describe the features of skill acquisition, such as the effect of practice on automaticity and the shapes of learning curves. Anderson has developed a line of production system theories that all fall under the name ACT. In 1983 he proposed a general theory of production systems called the ACT* theory. This theory was later (1993) improved to include a more specific architecture of the mechanisms of the production system. The theory was then extended to the ACT-R (R for rational) theory, which presents more advanced details of the model (Anderson, 1993, 2014). The experiments reported in this thesis are concerned with the basic skill acquisition concepts of the model, and will refer to Anderson's production rule theories under the broad heading of the ACT theory.

Anderson's (1982, 1983, 1987) ACT theory provides more details to extend Fitts and Posner's (1967) stage theory. For example, in the first phase of acquiring skill at performing a task, subjects acquire basic facts, statements and/or instructions about the task, known as declarative knowledge. These facts can be described verbally to others and are well known and identifiable to the individual. 'Chunks' of facts are then stored in working memory (Speelman & Mayberry, 1998). In the second (associative) stage declarative knowledge is then compiled into procedural knowledge. That is, declarative knowledge, which encodes our factual knowledge, transforms into procedural knowledge, which encodes cognitive skill. Furthermore, procedural knowledge also consists of task knowledge of the steps and procedures as the task no longer requires verbal rehearsal in working memory, and the procedures used are no longer available for verbal recall (Anderson & Lebiere, 1998). The

process of 'proceduralisation' is responsible for converting the declarative knowledge into production rules.

A production is a set of rules that are drawn upon for a specific cognitive act (Anderson, 1982). Anderson (2014, p. 4) states that "A production has certain boundaries; specific conditions and circumstances for which they apply and actions that are carried out when called upon. Production rules are if-then or *condition-action* pairs. The *if,* or *condition,* part specifies the circumstances under which the rule will apply". For example, a red traffic light is a signal to stop, therefore, IF the traffic light is red, THEN stop (Anderson, 1987). This is what Anderson (1992) terms the 'if then' rule. Anderson provides an example of a typical production rule for dealing with an addition problem:

IF the goal is to find the sum of $n1$ and $n2$

and $n1 + n2 = n3$

THEN say $n3$

There are some important features to note about the above production rule. The first is that there is a specific goal that has been identified. The second is the retrieval of a specific sum from long-term memory (Anderson, 1992). Anderson (1981, 1982, 1983) indicates that all productions have a set of conditions and actions or contexts based on declarative memory, and that as practice with executing these productions increases, refinement and specificity to that particular task increases. The process of composition, where several productions are combined into a single production, also speeds up performance.

The ACT theory suggests that problem solving involves a means-ends analysis (Anderson, 1993). That is, the problem solver determines the best strategy to reach an end or goal. If no adequate problem-solving state exists, the problem solver will search for a similar

problem-solving state. Research demonstrates (e.g., Pirolli & Anderson, 1985; Ross, 1984) that early problem solving is influenced by analogy to similar examples. This initial stage of problem solving is referred to as the interpretive stage, as it requires the recall of similar problem solving to be translated to the new problem-solving state. Verbalisation of critical analogy features is necessary as the learner rehearses task procedures and properties. As verbalisation ceases, a transition from the interpretive stage to the procedural stage occurs (Anderson, 1993).

The accessibility of declarative knowledge and the performance of procedural knowledge are dependent on the encoding processes. Practice strengthens the encoding of declarative and procedural knowledge so that strength grows as a power function of practice (Anderson, 1993). Power function improvements that occur in skill learning are controlled by the growth of strength. Skill is acquired with practice, and more importantly, the recognition of success in the execution of particular procedures consolidates successful performance through the development of knowledge (Anderson, 1982).

As mentioned above, the ACT theory proposes that skills are acquired via two forms of knowledge: *declarative knowledge* and *procedural knowledge*. Declarative knowledge consists of general information from past experiences and is characterised as being flexible and domain-general. This is where initial knowledge about performing a task begins. Implicit procedural knowledge is domain specific consisting of particular rules or procedures that become consolidated. For example, the previous traffic light example demonstrates the already acquired knowledge that a red traffic light is a signal to stop. So, where declarative knowledge holds representations of facts, procedural knowledge informs what actions need to follow; IF we already know that a red traffic light is an indication to stop, we must THEN stop. A process called compilation facilitates this reasoning. Compilation involves two processes: proceduralisation and composition.

The first process of proceduralisation is the creation of domain-specific productions based on declarative (domain-general) knowledge (Anderson, 1992). Once proceduralisation has occurred there is no need to consult declarative knowledge for task execution as a new set of productions (procedural knowledge) can be drawn upon. As this need to refer to declarative knowledge is reduced, the load on working memory should also be 'freed up' (Woltz, 1988). Composition is the collapse of sequences of productions into single step retrieval productions, which aids in efficiency and faster retrieval (Speelman & Kirsner, 2005). With practice, productions are strengthened and can be executed faster than newly formed productions.

The transition from declarative knowledge to procedural knowledge is illustrated in an example adapted from Speelman and Kirsner (2005), where a teacher describes an algebra solution to a student. The teacher may present the problem as follows;

$79 = 3x + 4$, the goal is to solve for '$x$'.

There are a number of sub-goals required to solve the problem. For example, the first step may be to isolate the '$x$' term on the right-hand-side of the equation. This will mean eliminating the "4" from this side of the equation.

$$79 + (-4) = 3x + 4 + (-4)$$

$$75 = 3x$$

Having achieved this sub-goal of isolating the "$x$" term on the right-hand-side of the equation, the teacher may move on to the second sub-goal, of eliminating the coefficient of the '$x$' term, which is 3. This is achieved by dividing both sides of the equation by 3:

$$\frac{75}{3} = \frac{3x}{3}$$

25 = x          This is then the solution to the problem.

The memory for such explicit instructions is considered declarative knowledge. It represents context specific knowledge that cannot be used to solve other problems. If the student was given another example, such as $85 = 4x + 5$, they could apply the same processes as the previous example, given the student recognised the similarities and usefulness of the previous solution (Gick & Holyoak, 1983). Thus,

$85 = 4\,x + 5$, the goal is to solve for '$x$'.

$85 + (-5) = 4x + 5 + (-5)$

$= 80 = 4x$

$$\frac{80}{4} = \frac{4x}{4}$$

$= 20 = x$

This example demonstrates how general problem-solving methods, such as analogy, translate declarative knowledge into action (Singley & Anderson, 1989).

The autonomous stage of Anderson's ACT theory concerns the strengthening of productions. As multiple productions may be applied to each situation, the probability of a particular production rule being recalled is a function of strength (Anderson, 1993). With successful application of a production strength is gained, however if a production is either not utilised or is used unsuccessfully it loses strength. Therefore, feedback mediates the strength

of a production. As strength of a production increases, the faster it may be applied. Thus, strength also contributes to a speed-up in performance, but not to the same extent as proceduralisation or composition (Anderson, 1983).

**The instance theory.**

Memory based accounts of automaticity, such as the instance theory, suggest that the transition from controlled to automatic processing reflects a race between the application of an algorithm to produce a response and a memory process that retrieves a response from past experiences (Logan, 1990). Logan's (1988) instance theory describes skill acquisition as improvements in performance attributed to an increased range of episodic representations. It is the automatic (fast) retrieval of an instance that results in improved performance, in contrast to the ACT theory where improvement with practice is the result of a refinement in procedural knowledge.

There are three premises that underlie the instance theory: obligatory encoding, obligatory retrieval, and instance representation (Logan, 1997). Obligatory encoding refers to the requirement of attention to form a memory representation, and that each processing episode results in a separate representation in memory. This involves memory of the stimulus conditions, goal state, interpretation of the stimulus conditions, the response, and the result of the response. Obligatory retrieval is the idea that attention to an item or event results in the associated memory of conditions, responses, and states being activated each time the event or item is encountered. Instance representation means that each encounter or episode results in a separate instance even if the instance is identical to many others in memory (Logan, 1997).

Performance can be described as skilful when it relies only on the automatic retrieval of instances. This requires some experience in the task in order to build and retrieve some instances. Logan's (1988) instance theory of automaticity describes automatic behaviour as

resulting from the accumulation of instances. Automaticity, then, represents a transition from algorithm computation (or multistep memory retrieval) to single step memory retrieval of episodes. This computation output is stored in memory so that future processing may bypass computation of the algorithm and rely entirely on memory retrieval. For example, in learning to solve addition problems such as: $3 + 3 = ?$  a student may start by counting the digits to generate an answer; however over time the solution to this problem will be stored in long-term memory as a single step, and the student will no longer rely on counting methods. The instance theory emphasises automaticity as a continuing process determined directly by the amount of training or practice (Logan, 1988).

Logan stipulates that in the race between the execution of the algorithm and the retrieval of an instance, whichever one is retrieved first controls performance. As practice increases the number of stored instances, the chance increases of an instance being retrieved faster than the execution of the algorithm. Performance becomes fast and automatic, resulting in a speed-up in the power function when performance is dependent on stored instances that are consistently recalled faster than the general algorithm. Thus, automatic retrieval of an episodic representation occurs through extensive successful practice.

One of the tasks Logan and Klapp (1991) developed to test the instance theory is the alphabet arithmetic task where participants are given a number of expressions consisting of alphabet equations for the first half of the alphabet. For example, expressions such as:

$A + 3 = D$        $C + 2 = G$

Participants are required to respond true or false to each expression. In order to perform the task Logan suggests that participants will start by counting through the alphabet, however, after significant practice participants will eventually be able to respond by remembering past solutions to expressions experienced before. Automaticity is then measured by the increase in

RT according to items on the screen. Facts that are recalled from past experiences are executed quicker than facts that need to be counted through the alphabet and have not been automatically recalled from memory. According to the theory, the number of instances ready to be recalled influences how quickly automaticity may be established. Logan and Klapp indeed found that automaticity was established relative to the number of arithmetic facts presented. That is, the number of items learned, rather than the amount of practice, determined how quickly automaticity developed.

Logan and Klapp (1991) also investigated whether transfer could occur to new items. That is, during training sessions one to 12 participants were trained on only one half of the alphabet arithmetic task, on session 13 participants were then given the same arithmetic style questions using the second 'untrained' half of the alphabet. They found a significant increase in RT between sessions 12 and 13. Logan and Klapp's findings support the assertion of the instance theory and automaticity-as-memory theories that only similar items will evoke responses from memory.

Automatic processing has been replicated and demonstrated many times in many different tasks, however what is missing from current automaticity and skill acquisition accounts is the level of awareness or directed attention involved in facilitating obligatory skill/memory retrieval of an instance. Kramer, Di Bono, and Zorzi (2011) suggest that diminished discriminability plays a role in automaticity. Kramer et al. investigated numerosity estimation in a visual motion task. A typical criticism of numerosity estimation findings is that by manipulating a collection of items, the physical dimensions also change, thereby increasing or decreasing the spatial area or density. Kramer et al. found that as numerosity increases numerosity items are either forced further into the periphery or closer together, so that both large and small numerosities may be underestimated.

**Skill Acquisition Theories Compared**

Logan's 'instances' and Anderson's productions both represent the stimulus context of the task, the goals of processing, responses executed and the outcome. However, the differences lie in the explanation of the development of automaticity. Logan's theory posits that new instances are created with each exposure (or practice), whereas Anderson's theory purports that automaticity is strengthened as memory is consolidated from multiple to single step productions. Also relevant to the development of automaticity, the theories differ in their explanations of learning curves and skill transfer.

Logan explains that the negative acceleration in the rate of learning occurs from the increase in the number of instances with practice. A negative acceleration feature of learning curves is produced by the retrieval of an instance faster than the previously fastest instance, the chance of this occurring gets smaller with increasing practice. Consequently the rate of improvement in performance diminishes. Anderson (1982) instead suggests the power law reflects compilation and strengthening processes during practice. It is the fine-tuning of productions that strengthens productions. The more successful experiences the stronger the production.

**Individual Differences in Skill Acquisition**

Reed (1931, p.1) summarised a theoretical question posed by Thorndike (1908): "Does equal training make a group of individuals more alike or more different in their achievement?" Thorndike's inquisition is an important consideration in skill acquisition and learning research as it questions the universality of learning. It cannot be assumed that individuals operate the same way that group data implies, that is, individuals may vary in processing, experience, and demand characteristics. Thus, conclusions made about

psychological occurrences using group data cannot be assumed to represent individual performance.

Skill acquisition is largely represented by a change in performance rate and gains. Data that are not represented by typical learning curves are suggested to be indicative of methodological or measurement problems (Ackerman, 1988), however, task characteristics may in fact be the chief problem in measurement error and therefore cannot be discounted or overlooked when analysing data. Differences in acquiring skills and task performance can be influenced by environment and variables outside of experimental control (such as individual factors and their interactions). Factors, such as task requirements, task difficulty, degree of prior learning and ability, and motivation may be key indicators to explain possible learning curve deviations.

In high stakes tasks performance pressure impacts on performance success and often causes below ability performance (Baumeister, 1984). The term *choking under pressure* describes this phenomenon. Although much research on choking is dedicated to high stakes situations, choking has been replicated in both real-world (e.g., Dohmen, 2008) and laboratory situations (e.g., Beilock, 2008). DeCaro, Thomas, Albert and Beilock (2011) describe choking under pressure phenomena as relating to the monitoring and control of attention. The pressure situation itself can lead to distraction, and explicit monitoring results in hindering working memory and attentional control. This links to motivational factors that mediate the amount of attentional resources and working memory features. A person's drive to fulfil accuracy or time goals would affect skill acquisition learning.

Conscientiousness has been suggested to influence learning ability in cognitive tasks. For example, Colquitt, LePine and Noe (2000) found conscientiousness to be positively related to motivation. Task approach, such as attending to accuracy demands of the task, may

slow down learning and result in learning curves not reaching asymptotic rates. Conversely, one who is overly reliant on speed of performance rather than accuracy will also indicate faster approaches to asymptote and may be interpreted as automatic. The implications here are two-fold, results may be interpreted inaccurately due to motivational features, or, results may be representative of differences in learning approach. That is, automaticity may not be achieved by all individuals due to motivational orientation.

Speelman and McGann (2013) highlighted the differences between group and individual data in an informal inquiry into the word superiority effect (where letter perception is more accurate when a letter is presented in the context of a word than when presented in isolation; Reicher, 1969; Wheeler, 1970). Data was collected over five years amongst undergraduate university students as part of a laboratory exercise (Speelman & McGann, 2013). The word superiority effect was found to be present in only half of the 500 participants (Speelman & McGann, 2013). Speelman and McGann suggest that in psychological research there is a tendency to focus solely on whether differences between means are statistically significant. In doing so, individual scores of the data set are assumed to reflect collective group results. Furthermore, Ruthruff, Allen, Klien, and Grabble (2008) also found individual variation in the automaticity of reading ability and attention, which they suggest may be due to individual differences in crystallised intelligence. Thus, caution must be taken when interpreting aggregate data. Individual trends in skill acquisition have been investigated by others, such as Ackerman (1987), Katzir, Ori, Hsieh, and Merian (2015), Phillips, Segalowitz, O'Brien, and Yamasaki (2004), Pellegrino (1988), and Stanovich (1980); however, no one has reported work on individual differences in the acquisition of automaticity.

Although there has been some research on individual differences in skilled performance, there is little research that directly focuses on whether all people, given the

same experimental conditions, attain automaticity on a particular task. For example, Ackerman (1997) investigated individual differences in skill acquisition. He found that in reanalysing several published findings individual differences exist between abilities, such as intellectual and cognitive abilities, and skill learning. However, Ackerman was concerned with individual differences in learning and individual differences in skill acquisition, not whether or not there are individual differences in attaining automaticity.

Individual differences in processing efficiency and the role of practice and ability have also been investigated by Pellegrino (1988). Pellegrino examined the issue of automaticity via measures of speed and accuracy of processing or task execution. He found that processing ability related to other abilities, specifically perceptual spatial ability. However, Pellegrino did not consider whether performance was automatic and how this related to ability measures.

In addition, research by Fawcett and Nicholson (1992) investigated individual differences in general learning deficits, specifically the ability to automatise without the need for conscious control, amongst children with dyslexia compared to non-dyslexic children. Fawcett and Nicholson examined balance performance of a range of motor skills whilst performing a secondary concurrent task of counting backwards. They theorised that children with dyslexia would have a break down in performance, that is, balance would be compromised, under dual task conditions. According to the Dyslexic Automatisation Deficit hypothesis, individuals with dyslexia may struggle to become completely fluent in both cognitive and motor skills, so, by introducing a secondary task, which is performed concurrently, attention would be distracted away from the motor skill balance task if performance had not been automatised. Individual data revealed support for the hypothesis with all dyslexic participants showing impairment in balance under dual task conditions, compared to only four of 19 non-dyslexic children who demonstrated a balance impairment.

Group data suggested a clear impairment on primary task performance for children with dyslexia, however, non-dyslexic children overall demonstrated automaticity of balance on both the primary and secondary task.

Whilst Fawcett and Nicolson's (1992) findings suggest that amongst individuals with dyslexia automatisation of tasks extends beyond the phonological skills in learning to read to motor skills, what is unknown is what may be contributing to a deficit of the acquisition of automaticity. That is, no further evidence can suggest why automaticity of balance failed to develop.

Whilst there have been many studies considering the quantitative individual differences in automaticity (e.g., Katzir, et al., 2015; Phillips et al., 2004; Ruthruff et al., 2008; Stanovich, 1980), they have been largely limited to how much practice and under what conditions automaticity develops. Yet individual differences in the rate of automaticity acquisition and how automaticity may affect performance has been overlooked. That is, previous research has not considered the qualitative difference in performance in the transition from controlled to automatic processes in individuals or whether automatic performance correlates to the ability to transfer skill.

Rowell, Green, Kaye and Naish (2015) investigated the pervasiveness of a particular processing strategy while people acquired a skill. The efficiency of reliably applying a particular effective processing strategy is suggested to be reflective of the development of automaticity (i.e., ACT and instance theory). Rowell et al. found that not all participants adopt a more efficient strategy; they do however, improve the application of a less-efficient strategy. Rowell et al.'s findings suggest that efficiency may differ individually, that is, one strategy may not be deemed efficient by another individual. Whilst this is an important finding in the individual differences in learning, the authors did not consider whether or not

the participants achieved automaticity. Identifying participants who were not automatic may provide further insight into what factors separate those who achieve automaticity and those who do not.

Schneider and Shiffrin (1977) suggest that under appropriate conditions and sufficient practice subjects have the capability to develop a skill to automaticity. However, researchers have not considered whether this capability is universal. A number of studies have attempted to draw conclusions regarding individual differences and automaticity; however few have considered whether or not automaticity has been individually attained. Research in the domain of automaticity has been devoted to determining how much practice and under what conditions *individuals* are able to develop automaticity, but none (to the author's knowledge) have determined whether or not automaticity has been achieved at an individual level compared to group data trends.

Automaticity is assumed to be achievable and universal in application; however, the Stroop effect has caused some concern over the misrepresentation of automaticity in a widely replicated phenomenon. The supposed ubiquity of automaticity affects how we interpret, diagnose, and implement automaticity, all of which have a profound effect on how we deal with learning. If automaticity is found to be sporadic in its attainment, this may change how we determine best learning practice. Given the current discrepancy in the interpretation of automaticity's occurrence and the recent attention to issues surrounding the use of group averages, it is questionable whether automaticity is as pervasive as the research suggests.

## Summary

This chapter has demonstrated that automaticity is acquired through different theoretical mechanisms according to the ACT and instance theories; however, each theory appears to support the importance of achieving automaticity for successful skill learning.

Furthermore, individual differences have been found to deviate from the typical learning curve and development of automaticity. This finding questions the universality of such theoretical conclusions. Educators are still striving for automaticity as best practice, and this position is certainly supported by the conclusions of Anderson (1982) and Logan (1988); however is learning to automaticity the best learning practice for all individuals? Chapter 4 extends the literature on skill acquisition into the domain of skill transfer in order to determine whether the transfer of training research indicates any role for automaticity in skill learning.

# Chapter 4: Transfer

Transfer of training describes the ability to apply skills learned in one situation in a new or changed context. This is of particular concern in education and training programs as skills are often overlearned in order to be reliably applied beyond the context in which they were learned. This chapter evaluates the transfer of training research in order to highlight the predictions that can be made regarding the transferability of automaticity. Possible prediction scenarios according to the literature will be presented with particular emphasis on transfer predictions based on Anderson's (1984, 1987) ACT theory and Logan's (1988) instance theory. The aim of this chapter is to determine whether the transfer of training theories and empirical evidence suggest that automaticity is transferrable.

Transfer of training is an important topic concerning precise and expert skills, such as medical surgery, pilot-training programs, tactical training units, and in domains such as sporting excellence and dance performance. Transfer research is typically concerned with determining how much transfer can be predicted based on previous training performance in order to improve the design of training programs. Transfer is traditionally referred to in three possible outcomes: positive, negative, and zero transfer. Positive skill transfer is generally referred to as the degree to which learning in one situation is useful in another (Speelman & Kirsner, 2005). That is, positive transfer is considered to be the ability to which one can apply knowledge, skills and attitudes beyond the original context (Anderson & Singley, 1993; Newstrom, 1984; Singley & Anderson, 1985, 1989). Negative transfer refers to a situation where knowledge developed in one context results in performance that is worse than if the task had never been performed (Anderson, 1987; Luchins, 1942; Singley & Anderson, 1989).

Finally, zero transfer describes the situation where knowledge gained in one situation provides no benefit in a new or second task (McKendree & Anderson, 1987).

The theory of skill transfer can be traced back to the behaviourist learning theory. Early research (e.g., Thorndike & Woodworth, 1901) was concerned with whether transfer did occur. Thorndike and Woodworth (1901) hypothesised that transfer is maximised to the degree that there are identical stimulus and response elements in the training and transfer settings. Thorndike's (1906) research was undertaken in response to the methods of education at the time that supported a broad view of transfer developed from the Doctrine of Formal Discipline (Singley & Anderson, 1985). The doctrine was a general educational approach that suggested observation, attention, discrimination, and reasoning are 'faculties' of the mind. Much like they way we would exercise a set of muscles the doctrine suggested that the mind should be 'trained' independent from context for some courses (Singley & Anderson, 1985). General transfer of skill from this perspective suggested that training in one domain would extend transfer beyond that context. For example, tasks that involve general reasoning faculties, such as chess, should transfer to other tasks such as computer programming. Thorndike extended this general view of transfer some years later to show a much narrower transfer scope than previously proposed by the formal doctrine (Singley & Anderson, 1985). The idea of identical elements limits transfer to only tasks that shared common elements so that transfer can be determined by the level of similarity between training and transfer components (Subedi, 2004). Transfer may then be considered a function of the number of common elements between the two tasks (Gray & Orasanu, 1987). Thorndike (1906, p. 246) stated that "the mind is so specialised into a multitude of independent capacities that we alter human nature only in small spots, and any special school training has a much narrower influence upon the mind as a whole than has commonly been supported". Thus, training in one kind of activity would transfer to another, only if the activities shared common elements.

Declarative knowledge, the knowledge of facts or static knowledge, was, according to Yum (1931), a significant variable in transfer where the similarity of stimuli, such as in meaning or sound, would facilitate complete positive transfer. Conversely, if the required responses in two tasks were similar, not the stimuli, then transfer was negative (Bruce, 1933). These studies primarily considered facilitation and interference in declarative memory as a predictor of transfer success. Some have suggested (e.g., Gick & Holyoak, 1980; Hinsley, Hayes, & Simon, 1977) that individuals are quite poor at transferring knowledge and some research (e.g., Bott, 1979) has shown that people may even choose inappropriate knowledge to perform the transfer task and performance may suffer.

Empirical research supports the usefulness of identifying identical elements as a means of increasing the retention of both motor (Crafts, 1935; Gagne, Baker & Foster, 1950) and verbal behaviours (Duncan & Underwood, 1953; Underwood, 1951). Thorndike's experiments (Thorndike, 1922; Thorndike & Woodworth, 1901) showed support for the identical elements theory, however, some transfer of skill was also demonstrated even when identical elements were not obvious, suggesting that transfer may not be limited to only identical task components. The concept of shared skills or skill overlap may seem plausible, as there are many tasks in which transfer could be a function of shared training and transfer task components. For example, arithmetic facts or simplification of equations may utilise a specific rule that could be used in transfer contexts. Furthermore, underlying units of knowledge of language comprehension may also be retained and called upon in transfer situations (Singley & Anderson, 1989). However, failure of transfer does occur despite shared or skill overlap, thus the interrelationship of shared components may be difficult to conceptualise according to Thorndike's identical elements theory. Furthermore, as the notion of transfer implies flexibility and adaptation of learned skills, Thorndike's identical elements theory would appear to be incompatible with the stimulus-response pairing of elements

concept. For transfer to be expected to occur in only situations where the same responses to the same stimuli are required, the individual may simply be doing the same as before rather than something new and adaptive (Singley & Anderson, 1989). Singley and Anderson (1989, p. 6) further suggest that "no two situations are truly identical; they are merely perceived as such psychologically", which further questions the real world application of Thorndike's theory as learning situations rarely provide identical situations, contexts, or conditions.

## The ACT Theory and Transfer

The modern version of Thorndike's identical elements theory is referred to as "common elements", which is based on Anderson's (1983) ACT theory of skill acquisition. The ACT theory (as discussed in Chapter 3) encompasses a general theory of skill acquisition, thus, skills are suggested to be general in nature and can be applied to contexts beyond the acquired context. What mediates transfer performance is the number of shared components between the learned context and the new context. That is, transfer is dependent on the degree to which productions acquired in one context can be used in the transfer context. As explained in Chapter 3, skilled behaviour results from the compilation of declarative knowledge (facts) about domain procedures. These procedures are triggered under highly specific conditions, so that a procedure learned in one part of a domain will not be used in another part of the domain unless the conditions of use of the procedure are identical in the two cases. Thus, for transfer to occur between two tasks, the tasks must share common procedures or elements.

Transfer is expected to be high and positive when an individual goes from one set of problems to another set of similar problems that can be solved using the same productions. This idea encompasses the fundamental principle of the ACT theory, the "use specificity of knowledge" (Anderson, 1987, p. 26). It is not knowledge that is acquired with training and

practice that is transferred, as implied by the identical elements theory, but a particular *use* of knowledge (Anderson, 1993). Skill transfer may then be considered a higher order process than acquiring the skill itself (Anderson, 1982; Singley & Anderson, 1985). The use specificity of the knowledge principle predicts that there will be little or no transfer between sub-skills within a complex skill domain when knowledge is used in different ways, even though the sub-skills might rest on a common body of declarative knowledge. Thus, the way in which the common elements theory differs from the identical elements theory is in the more abstract identification of cognitive elements than typically associated with Thorndike's stimulus response elements.

There is ample empirical support for the general or common elements theory. For example, Singley and Anderson (1985) investigated transfer between text editors: ED, EDT, and EMACS. The goal structure was identical for ED and EDT (they both utilised the same general method of editing), but the surface structure was different (they used different command names for the same functions). The goal structure was different for EMACS, but the surface structure was similar to ED and EDT. The prediction was that there would be near perfect transfer between text editors within the goal structure, which was identical (i.e., ED and EDT), and little transfer when the goal structure was different (i.e., between ED/EDT and EMACS).

Singley and Anderson (1985) based their experiment on the identical production rule theory. In order to predict the exact amount of transfer demonstrated by the editors, Singley and Anderson encoded each of the editors in a production system model based on Card, Newell and Moran's (1983) method for analysing a task. Whilst the three models had several identical production rules, specific keystrokes controlling the edits differed between editors. The two line editors also demonstrated greater overlap in production rules than with the screen editor. To account for this, a percentage of production rule overlap was calculated

taking into account the frequency of the production rule. The results supported the prediction that near perfect transfer between text editors would occur when the goal structure was identical (i.e., between ED and EDT), and little transfer when the structure was different (i.e., between ED/EDT and EMACS).

A study by Kieras and Bovair (1986) investigated the transfer of related procedures for operating a control-panel device. Participants read a series of step-by-step instructions to get an indicator light to flash. It was expected, based upon Keiras and Bovairs' (1983) previous work, that as the procedures were related, some transfer of training might occur from procedures learned earlier. Strong positive transfer occurred when the individual production rules from one procedure could be re-used in the next procedure. Kieras and Bovair's findings suggest that participants were able to translate instructions into a declarative representation of a complete production rule, which could then be related to other representations. When an identical representation existed it could then be reused. This would appear to support Anderson's (1982) theory where declarative representations can be interpreted by a general production rule for instruction. That is, participants are able to filter new and learned material to formulate a higher order production set by composing or chunking multiple learned steps into smaller more efficient production representations.

Frensch (1991; experiment two) investigated the process of composition in Anderson's ACT theory. According to ACT it was hypothesised that when trained on a six-step mental arithmetic task, participants would learn to chunk or compose multiple productions together, which would result in faster performance in transfer tasks that shared more steps with the original task. Thus, performance would be a function of shared original task components. The results supported the prediction that participants were faster on the second task compared to the first task due to the increase in composed steps from the original

task. Thus, the process of composition appears to play a vital role in the acquisition of skill and transfer of training.

Models of transfer based on skill acquisition theories assume learning involves a set of general problem-solving skills, and a process of specialisation of general knowledge to a transition to efficient knowledge specific to a particular task (Anderson, 1982, 1987; Logan, 1988; Taatgen & Anderson, 2002; Taatgen & Lee, 2003). That is, knowledge is separated into fixed general knowledge and task specific strategies. Others (McClelland et al., 1986) also support this view of general and task specific strategies in neural network models of complex tasks.

Although there appears to be empirical evidence supporting the compilation and production rule conceptualisation of Anderson's ACT theory, there are a number of issues with the production rule notion. For example, production rules are a very complex representation and prove to be problematic when trying to determine how sets of rules are represented in the brain (Taatgen, 2013). Furthermore, the theory also assumes that production rules are highly task specific; this does not indicate how skills may also be interrelated (Taatgen, 2013). Two assumptions of the specificity of production rules are also dubious: 1) a production rule typically specifies multiple elementary comparisons and multiple elementary actions; 2) specific knowledge elements are held by production rules.

According to the ACT theory, transfer may be assumed to be a fixed and calculated state based on the number of similar elements; however, as Taatgen (2013) identifies, predicting transfer based on shared components is ambiguous and problematic. Transfer may be instead dependent on other factors, such as the amount of expertise in particular skill sets. The amount of transfer to be expected may vary with the amount of expertise achieved, so

that higher levels of expertise may present a greater likelihood of transfer or skill retention due to more skill experience.

Frensch and Geary (1993) investigated the effects of training on transfer performance. They devised a task where 17 out of 21 productions used in a simple addition task were also used to form a complex addition task. However, Frensch and Geary found medium practice groups showed larger improvement on the complex problems than high practice conditions. They concluded that practice does affect solution time, yet, practice which was expected to lead to expertise, did not appear to increase transferability of production rules. However, it may be possible that participants were already skilled at simple addition so that further practice may not have been of any benefit. Anderson and Fincham (1994) found similar results in respect to practice and transfer as Frensch and Geary reported. Using an analogical reasoning task, limited skill transfer was demonstrated between a rule-only practice task to a declarative example-transfer test. Skill transfer was not retained some days after the initial transfer trial. Anderson and Fincham's results indicate that whilst immediate transfer of skill was demonstrated, skill transfer did not appear to benefit learning overall with the transferred skill quickly diminishing soon after the initial trail.

Whilst there is some empirical evidence for Anderson's (1982) theory that skill transfer can occur beyond the context in which the skill is acquired, the role of other variables, such as expertise or automaticity, appears to be missing from the theory. Variation in transfer performance cannot be accounted for by referring to ambiguous production rules in the ACT theoretical framework. In line with Taatgen's (2013) proposition, expertise or the acquisition of automatic performance needs further investigation. The amount of transfer may be mediated by the amount of skill acquired. Thus, it is plausible that automaticity may be a contributing variable in the transfer as automaticity of component skills are suggested to be required for expert performance (Samuels & Flor, 1997).

**Transfer predictions of the instance theory.**

The instance theory of automaticity (Logan, 1988, 1990) suggests that skills are specific to the context in which they are acquired and may be difficult to transfer to a new context. Thus, based on the parameters of the instance theory it is predicted that no transfer can exist between different tasks. The theory revolves around the retrieval of instances, therefore if there are no instances to call upon then there would be no transfer of skill. That is, if the new task involves specific events encountered in the old task, transfer is possible, however, if new stimulus conditions are present there will be no instances to draw upon, and so performance will rely on the execution of an algorithm that will result in performance similar to pre-practice levels.

Many studies to date support Logan's instance theory and have demonstrated the limit of transfer as implied by the theory. A classic example is the alphabet arithmetic task discussed in Chapter 3. Participants were given statements with one half of the alphabet (i.e., A–J or K–Z) and were asked to identify whether the answer was true or false (Logan & Klapp, 1991). Initially, participants were expected to count through the alphabet in order to determine the truth of a statement, but with practice the counting algorithm could be replaced by memory for the alphabet-arithmetic facts. However, when asked to perform the equations using the other half of the alphabet (i.e., K–Z or A–J) very little transfer resulted. This should not be surprising because, when participants were exposed to problems involving letters from the second half of the alphabet (as opposed to the first half of the alphabet in the initial task), they would have no relevant instances stored in memory. They would therefore be required to resort to the counting algorithm again. As a result performance time would increase. Logan (1988) suggests therefore, that skills are item-specific; that is, skills acquired are constrained to the specific items experienced during training. Thus, no transfer can occur between items that have not been experienced before. Interestingly, some amount of positive transfer did

occur in Logan and Klapp's experiment—performance times with the second set of items did not return to the slow pre- practice performance times.

Lassaline and Logan (1993) investigated automaticity and transfer in visual numerosity in order to determine the specific nature of memory representations. Lassaline and Logan's (1993) task consisted of five unique patterns for each level of numerosity (i.e., pictures of dots, ranging in number from six to 11). Participants were required to indicate on a response pad how many dots were displayed as quickly as possible without looking at the response pad. It was expected that participants would start off by counting each item, and with practice they would recognise the picture and remember the appropriate response rather than count the items. Lassaline and Logan conducted seven experiments in which they altered the transfer phase to identify which task elements were held in memory and were successfully transferred. The first experiment involved 12 training sessions of five unique patterns for each level of numerosity (6, 7, 8, 9, 10, and 11). In session 13 a transfer task was introduced with a new set of numerosity configurations.

Numerosity judgement was suggested to be a simple task in which RT would demonstrate a distinction between a counting algorithm and the memory retrieval process (Lassaline & Logan, 1988). That is, initial counting strategies would reflect greater RT, as the number of elements displayed on the screen also increased. RT was found to be a function of the number of elements, where response patterns reflect a positive linear function with a mean slope of 300 ms per element from four to 10 items (Chi & Klahr, 1975). In session 13 where a new set of numerosity configurations was introduced performance was disrupted. RT performance increased to the level obtained during early training, indicating evidence of item specific learning (Lassaline & Logan, 1993).

In Lassaline and Logan's (1993) second experiment, training was reduced to four sessions. The same spatial arrangement of numerosity configurations was utilised, however, instead of asterisks different single letters (i.e., A, E, I, O, or U) were arrange in the configuration. The transfer task introduced three different conditions: old/old – where patterns were the same as those used during training; new/new – where new patterns only seen in transfer with different spatial arrangements were used with a new set of target letters (i.e. 'E' instead of 'A' previously used); and old/ new – where the same patterns and spatial arrangements were utilised with different letters than those seen in training. Results indicate that learning was item specific as new/new transfer performance returned to pre-beginner levels. Furthermore, old/new and old/old transfer performances were not significantly different suggesting that element identity for item specific learning is not necessary in this type of task. In the following five experiments, elements such as colour of items and degree of rotation of configurations were changed. It was found that new/new items did not transfer successfully and that old/new items transferred successfully as long as the item changes were not too different to the original transfer task.

Lassaline and Logan found that memory assisted algorithmic transfer did not occur with new items; performance returned to early training levels indicating that learning is item specific. Lassaline and Logan (1993) concluded that the aforementioned results demonstrate item specific learning and limited transfer of memory-based learning. However, as transfer was only tested over one session it is difficult to conclude what effect automaticity has on transfer and thus overall learning. Although Lassaline and Logan's intentions were to investigate the specificity of learned items on transfer in order to determine which elements are held in memory, testing transfer from only one session does not provide enough insight into the nature of transfer nor does it provide insight into the effect or recovery of a transfer disruption.

Green (1997) too found that performance did not slow to levels seen in pre-training. Green used a visual numerosity task where participants were presented with eight to 10 items on screen. They were then asked to count the number of items displayed. These patterns were repeated during the training phase. In the transfer phase patterns differed from the original ones presented in training by either overall patterns (experiment one) or items used in the configuration (experiment two). As the patterns differed in some way in transfer, Green predicted that performance would be disrupted. Whilst Green's prediction was supported, performance was not disrupted in the manner predicted; it was expected that as only item specific changes were made, some general learning of the configurations could occur resulting in partial skill transfer, however participants showed a large cost to transfer performance with times slowing to near session 1 response levels. The results suggest that only item identity information, instead of pattern encoding information, was used to support automatic responding.

Logan (1998) investigated what is learned during training and what can be transferred. A category search task was used where participants were asked to search through one word or two word displays for items of a target category. Target items appeared in the same locations during training trials, however in transfer trials item locations were changed. Based on the item specificity aspect of the instance theory it was predicted that performance would be disrupted due to the change in item location. However, what was found was that although visual information is automatically encoding during training, transfer was dependent on the number of words associated with each location. Logan referred to this as cue overload. In experiments one and two, location change did not impact upon transfer performance. In experiments three, four, five and six, cue overload was investigated to determine whether the non-retrieval of location in transfer was due to too many words associated with too few locations. Significant sensitivity to location change was found. Thus, Logan concluded that

individuals encode locations of items as instances resulting in impaired performance when locations are changed in transfer.

Logan's experiments support claims of item specific transfer, however caution needs to be utilised in generalising about the nature of transfer. Speelman and Kirsner (2005) suggest that item general transfer occurs under varied conditions, thus it is the task conditions that determine transfer not the nature of skill. Speelman and Kirsner suggest the contexts of training experiments are in general too restrictive and reflect artificial conditions, which cannot reflect the real life applications of skill transfer, thus making it difficult to predict transfer from training performance or elements. Instead they suggest that it is the task conditions that led to Logan's (1988, p. 63) findings of item specific transfer: "skills do not have a fixed nature, but rather develop as an adaptation to the environment."

### Predicting transfer from training performance.

Transfer of skill research has primarily been concerned with the conditions that facilitate transfer; yet, this has produced varying positions (Speelman & Kirsner, 2005). An accepted generalisation is the overlap in knowledge between the learned and new skill—the greater the knowledge overlap, the more transfer is expected to occur. However, central to the issue of skill transfer is the amount to which skills are automated or how easily skills/components/instances are retrieved from memory. As suggested by Logan's instance theory, an algorithm needs to be retrieved in a fast efficient manner to be utilised in a task, thus the fastest retrieval wins the race and is used. Anderson's ACT theory posits that the usefulness of one set of skills for another task mediates transfer performance. Automating task productions and creating task general skills leads to automated execution of a skill to another task.

Previous studies (e.g., Speelman & Kirsner, 1993; Speelman, 1995) have tried to predict transfer performance based on training performance with little success. According to the ACT and instance theories skilled performance is governed by the power law of learning (see Chapter 3) and is characterised by automatic activation of responses from compatible stimulus conditions (see Chapter 2). Thus, both theories would consider if task conditions and performance goals were the same as in the training task (Speelman et al., 2011). In most cases then, this would be a continuation of the power function that describes the improvement in performance during training (Newell & Rosenbloom, 1981). This was evident in Speelman and Kirsner's (1993) findings. They found that when task conditions remain unchanged, performance for 288 trials was able to predict the subsequent pattern of improvement. Given that old skills can predict future performance on the basis of a power function description of past performance, transfer performance may also be predictable.

Speelman and Kirsner (2001) investigated whether transfer performance can be predicted from training performance and whether or not old skills continue to improve in the context of new tasks, according to the power function that describes their original improvement. Speelman and Kirsner utilised a two-part task design where each task was performed in sequential order. Participants were trained with some of the sub-tasks and then introduced to a new task that involved the whole set of sub-tasks. In the new task the old skills that were developed to perform the original set of sub-tasks could be executed independently and prior to attempting the new set of sub-tasks. What they found in the first two experiments was that the complexity of the transfer task affected how much transfer could be predicted. The experiments indicated that any change in the transfer task would affect the performance of 'old' skills causing a disruption of transfer performance in 'new' tasks. In the third experiment the amount of practice and the change of complexity were investigated. Based on these findings it was questioned whether performance of 'old' skills

are bound to specific task constraints. Speelman and Kirsner predicted that by increasing practice trials and establishing automaticity in training, 'old' components would become embedded or 'tied' to the constraints that the 'old' skills were learned under, and thus a greater disruption would be seen due to the establishment of greater automaticity. However, only partial transfer occurred, contrary to Speelman and Kirsner's predictions. These findings also contradicted the interpretations of the ACT theory and instance theory, where performance may be suggested to continue in accordance with power functions that describe training performance. Even though a slight disruption of performance may be expected, learning should still continue in accordance with training performance.

It is notable that by altering task complexity, Speelman and Kirsner (2001) also altered the visual context of the task. Speelman et al. (2011) suggest that this could have altered the conceptual context by changing the number of calculations, resulting in the disruption of performance. Therefore, it is not possible to determine whether it was the visual appearance or a change in perceived complexity of the task that was responsible for the transfer disruption.

Speelman et al. (2011) also found an immediate disruption of performance when changing the conceptual context of 'old' target problems to that of a 'new' context during a transfer phase whilst avoiding any changes to the visual context of the task. Performance was predicted to continue in accordance with power functions that described training performance, however Speelman et al. found performance of 'old' skills was disrupted during 'new' task additions. Such a result is a challenge for the theories of Anderson (1987) and Logan (1988). According to these theories, it can be interpreted that performance of 'old' skills should remain the same and demonstrate complete transfer when 'new' skills are added because well learned skills suggests a more durable and reliable recall of how to perform the task that should withstand all minor context changes. However, performance in transfer trials

does not seem to support the claims of prominent theories as skill performance can be disrupted by the presence of a novel task. What was interesting in Speelman et al.'s findings was that by dispersing 'new' (or distractor) tasks amongst 'old' tasks where both the transfer and training conditions were the same, performance of the 'old' task was disrupted despite the fact that nothing in relation to task strategy was altered. The way in which the participants interpreted the changed task in transfer could be influenced the performance of old skills. Thus, Speelman et al.'s findings could suggest that even minor subtle changes may disrupt the reflex like nature of automatic skills, that is, of course, if participants had developed automatic performance.

Speelman and Parkinson (2012) utilised a similar experimental design as Speelman et al. (2011) using a two-part task: part one, a simple 'correct' vs. 'incorrect' answer to a target multiplication problem (e.g., 6x2) ; followed by part two, a distractor problem where participants were asked to add or subtract a number from part one's answer. What Speelman and Parkinson found supports the findings of Speelman and Kirsner (1993) and Speelman et al. (2011). That is, any change to part two of the task in transfer trials results in a disruption of performance on part one of the task; thus, the change in the distractor problems appears to increase RT on the target problem in part one. On the basis of these findings, in addition to the findings of Speelman and Kirsner, and Speelman et al., the disruption observed during initial transfer trials appears to contradict the predictions of the most prominent skill acquisition and automaticity theories.

Healy et al. (2005) investigated whether secondary task changes impact upon successful transfer of learned skills. Research (e.g., Battig, 1972, 1979) has found that for retention of learned skills to be maintained and transferred, learning should contain conditions with interfering information. Healy et al. utilised a duration-production performance task where the primary task in training involved participants learning to produce

fixed intervals of time expressed in arbitrary units. In the transfer trials, new intervals of time were introduced with previously learned intervals from training. There were three different training conditions; a *control* condition where no secondary task was introduced; an *easy* condition where participants were given a single letter of the alphabet and were required to simultaneously repeat the letter aloud in addition to completing the time duration task; and a *difficult* condition where participants were required to recite the alphabet backward by every third letter starting from the letter cue given at the beginning of each training trial (i.e., if the cue was 'w' the order of recital would be 'w'. 't', 'q', etc.).

Healy et al. (2005) found in experiment one that the difficult task condition resulted in disrupted transfer performance, conversely, the easy task condition demonstrated greater transfer of time duration learning. Healy et al. suggested this was due to the fact that operations used during difficult training could not be used in transfer, this would appear to support the common elements and specificity of training theories from the ACT and instance theories. Further to this, experiment two found that participants who experienced changes to the secondary task in transfer also demonstrated a disruption in transfer performance to levels observed in session one. The results of Healy et al.'s study suggest support of the specificity of training principle and further suggest that despite training performance improvement context changes can impact upon transfer performance.

Thus far, a picture has emerged that transfer is possible if the transfer task components are close to the ones experienced in the training conditions. Predictions regarding transfer have typically been informed on the expectation that automatic performance results from extended practice. The end product of extensive practice and skill learning can be automaticity, and the widely accepted view is that learning a skill, such as learning the times tables, will enable performance in other tasks, such as higher order division and using formulae. Automaticity is suggested to be demonstrated as a decreased

power function that describes training performance (Logan & Etherton, 1994), and is implied to be an expected outcome of practice performance, but it has not yet been noted as a related factor in predicting transfer performance. The aforementioned studies have not explicitly considered whether the degree of automaticity may influence the transferability of training performance. The current inconsistencies in the research call into question whether automaticity should be considered a variable in the transfer of skill. Do automatic skills transfer easily? Current theories are unclear on this position.

**Predicting transfer based on automatic training performance.**

Automaticity is considered the end product of extensive training practice, and is often implied to be transferrable or useful in other contexts (i.e., times tables are typically practiced for rote recall to be used in other more difficult mathematical problems). Yet, no theory explicitly considers the relationship between automaticity and transfer or questions whether automaticity influences the transferability of skill. This is surprising given that automaticity and transfer appear to be implicitly tied in the predictions of transfer performance. Given that automaticity requires extensive practice it is questionable whether in an educational context, it is worth waiting for automatic skills to develop in students before moving on to more complex skills. In other words, do automatic skills transfer more easily than less automatic skills? This is generally of concern in educational and vocational settings for both adults and children. A central issue explored in this thesis is what factors affect transfer, and specifically, how an underlying assumption surrounding skill acquisition, the development of automaticity, affects skill transfer.

As demonstrated in the literature, skills acquired in one situation may also be transferred to another. Skill acquisition theories suggest that effective and efficient learning will produce automatic component parts. Accordingly, automaticity is considered an essential factor in learning to master basic level skills prior to attempting more complex skills (Chase

& Simon, 1973; Logan, 1985). For example, students are often trained on arithmetic facts, such as multiplication, so that they can be automatically retrieved in order to free up cognitive load before attempting harder math combinations such as division (Baroody et al., 2009; Cummings & Elkins, 1999). Furthermore, skill transfer has been demonstrated to occur beyond the conditions in which skills are acquired (e.g., Anderson, 1982). Yet there is a lack of empirical evidence that transfer is explicitly facilitated by automaticity. As it stands some evidence points to transfer being inhibited by automaticity, whereas other evidence points to a facilitative effect. Educational research (i.e., Baroody et al., 2009; Cumming and Elkins, 1999) advocates that automaticity is essential for basic literacy and numeracy to develop higher-level cognitive skills, however, this assumption appears to be based only on inference. To date no studies have considered whether fundamental numeracy skills have been developed to automaticity or how this might affect (or limit) achievement in the long term. Although, this assumption applies that learning is a staged process, where the aims is that a trainee will master one set of skills before being introduced to the next set, there is a disparity between the theoretical expectations of skill acquisition and the empirical findings in the transfer of training research that supports this view of 'waiting' for automaticity..

**Transfer is inhibited by automaticity.**

As presented in Chapter 2, the common view of automaticity lacks a clear and consistent definition. Automaticity has been described as the uncontrollable response to a given stimulus, which prevails in all contexts or situations in the absence of conscious awareness or effort (Hasher & Zacks, 1979; Posner, 1978). Schneider and Shiffrin (1977, p. 2) suggest that an automatic process is difficult to "suppress, modify, or to ignore", implying that automaticity is reflexive. Yet it is unclear whether automaticity is bound to the context under which it was established, resulting in 'fixed', context bound execution that is resistant to modification. As stated in Chapter 3, Hatano and Inagaki (1986) suggest that expert skills

can be categorised into two types: routine expertise, and adaptive expertise. What Hatano and Inagaki's theory of expertise suggests is that automaticity may involve highly constrained skills that are only useful under the conditions in which they were acquired. Thus, practice leading to automaticity creates context bound skills that are unaffected by context changes and may be considered inflexible.

Automaticity up to this point has been depicted as a process that is stimulus driven, occurs without intent, is capacity free, and cannot be derailed or interrupted; this definition of automaticity questions whether automaticity is a limiting factor in some situations where flexible adaptable skill is required. From the literature presented in Chapter 2, this question remains unanswered.

**Transfer is facilitated by automaticity.**

Practice is suggested to increase transferability, and a well-learned task can successfully transfer (Keiras & Bovairs, 1983). But there appears to be no empirical discussion of automaticity as a variable in influencing transfer. In the literature spanning skill acquisition, expertise and educational research, automaticity is implied to be an enabler of transfer. That is why children are rigorously taught to memorise sight words, simple mathematical problems such as times tables, and even musicians are trained so that recall of musical notes are not needed to be considered when attempting to improvise a new tune. Furthermore, reading is considered a highly automatic skill. Expert readers do not need to consider the identity of a letter, word composition, or meaning when they encounter a new reading context such as font style, or format. Thus automaticity would appear to facilitate transfer.

There has been some suggestion that practice reduces context changes on a secondary task. Ruitenberg, Abrahamse, De Kleine, and Verwey (2012) investigated context

dependence of a memory based sequence task. Participants practiced two 6-key letter sequences presented in either blue or yellow, given at random order. A go/ no go signal was given with a fixation cross in either red (withhold sequence/ no go) or blue.(repeat presented sequence/ go). There were two practice conditions; in the first *limited practice*-condition participants completed 50 practice trials, and in the extended practice condition participants completed 250 practice trials per sequence. After a 2 minute break participants performed the sequences in one of three context conditions; in the same *context condition*, the sequences were presented in the same colours as practice; in the *reversed context condition*, the sequence that was formerly presented in blue was now presented in yellow; and in the *novel context condition* the learned sequences both were presented in red. Ruitenberg et al. found that performance was equally impaired when the stimulus colour was reversed, whereas, sequencing performance was unaffected in the novel context condition relative to the same context condition. Performance impairment in the context reversal condition demonstrated a reduction in RT in the limited practice group, compared to the extended practice group. However, this group result was not considered statistically significant. They concluded that context dependence decreases as practice increases.

Interestingly, Ruitenberg, Verwey, and Abrahamse (2015) found that context sensitivity is facilitated by practice. That is, context dependent retrieval becomes context sensitive to practice, compared to Ruitenberg et al. (2012) who suggest context dependent filtering decreases with practice. In Ruitenberg et al.'s (2015) study participants were asked to respond to the location of a target that was presented in one of the four fixed placeholders that were horizontally aligned. At each trial a distractor (differing in colour from the target item) was presented within another placeholder, creating stimulus response interference. Rutinberg et al. found participants were able to filter out the distractor, however, performance declined when the relationship between target and distractor locations (i.e., the context) was

changed. Nevertheless, with practice this context effect is found to decrease (e.g., Hikosaka et al., 1999; Verwey, 1999), where sequencing performance transitions from stimulus driven to being representation driven. Thus, performance develops an internal representation (e.g., motor chunk) in response to the first stimulus of the sequence leaving both task relevant and irrelevant information to be ignored (Ruitenberg et al., 2012). However, context may still affect task performance if the context is similar or no clear distinguishability can be made; then, context dependent performance may be due to associative learning (Anderson et al., 1998; Wright & Shea, 1991). During sequence acquisition, continuous pairing of context features with sequential information causes associations between task-relevant and irrelevant information, just like the continuous pairing of two stimuli can result in associations.

Simulator training has repeatedly demonstrated that skill can transfer beyond training situations into applied settings (e.g., Stefanidis, Scerbo, Montero, Acker, & Smith, 2012). For example, Stefanidis, Scerbo, Sechrist, Mostafavi, and Heniford (2008) investigated whether novice students in laparoscopic simulator training develop automaticity (defined as the ability to multitask in this experiment) with accumulated experience. Stefanidis et al. (2008) found that secondary task performance improved with practice as participants became more comfortable and proficient with the primary laparoscopic task. Furthermore, they found that while some signs of automaticity were evident such as simulator time improvement and increased accuracy proficiency, the point which other paradigms use to determine when to terminate simulator training, learning of the primary task was still occurring as indicated by continued improvement in secondary task performance. That is, the complete attainment of automaticity required more time with the practice simulator. These results suggest that for transfer to occur, complete automaticity may not be required as many studies have demonstrated successful transfer of simulator learned skills. Such observations question whether automaticity is required for skill transfer.

## Summary

This chapter has demonstrated that research concerning skill transfer has previously been limited to examining the conditions under which transfer is likely to occur, with many contradictory findings (Speelman & Kirsner, 2005). As described by skill acquisition theories, transfer is likely to occur if skill overlap occurs between the training and transfer tasks, whilst other research suggests that the nature of training can affect the likelihood of transfer (e.g., Speelman & Kirsner, 1997). No previous research has examined the relationship between automaticity and transfer, even though it is implicitly implied in the skill acquisition theories as an important part of the learning process. It is conceivable then that if more practice leads to greater skill transfer, then if a skill is automatic greater transfer would be expected. Speelman and colleagues have found in their investigations of transfer predictability that a well-learned task does not seem to lead to successful complete skill transfer.

# Chapter 5: Experiments

## Introduction to Experiment One

Due to considerable inconsistency in the literature regarding transferability of automated skills (reviewed in Chapter 4), the principle focus of this thesis was to clarify whether automaticity facilitates or inhibits transfer. In an education setting, what should a teacher be aiming for during training: knowledge that is automatic and easily retrieved or knowledge that is context rich with an understanding of when and where to apply it? Such questions are essential as we strive to find the best solution to learning a vast array of information in a relatively short amount of time. For example, in the learning of mathematical skills in early childhood should a child be trained on arithmetic facts so that they can be automatically retrieved when needed before moving on to solving multiplication problems? In doing this, are we in fact waiting too long and surpassing the optimum time for moving on in task complexity and so ultimately slowing down learning? These questions concern the nature of transfer and the variables that affect when it does or does not occur and questions the role of automaticity in skill acquisition and transfer.

In order to inform subsequent experiments, the first study in the present program of research was conducted to test the experimental design. Analysis of individuals' data regarding performance patterns of automaticity and transfer was included to determine whether individual characteristics could predict the likelihood of successful transfer, and also to determine the pervasiveness of group data trends.

In experiment one, there were two parts to each trial. The two parts were designed so that the first part of each trial was identical in each phase of the experiment. In the first part of each trial — the primary task— participants were presented with a configuration of asterisks, to which they were required to make a decision as to whether there were six, seven,

eight, nine, 10, or 11 items by pressing a corresponding key. In the second part of each trial — the secondary task — participants were presented with a new configuration, which was the same configuration presented in the primary task but some asterisks had either been added or subtracted from the original configuration (see Figures 3 and 4). Participants were required to indicate whether the resulting number of items was odd or even by pressing the corresponding key on the response box.

| Training trial | Primary task | | Secondary task | |
|---|---|---|---|---|
| | *    *     *<br><br>*  *     *<br><br>How Many Stars? | | *    *    * *<br><br>*  *     *<br><br>Are the stars odd or even? | |
| * | | | | * |
| Fixation Point 500 ms | Answer 6 | Blank Screen | Answer Odd | Fixation Point 500 ms |
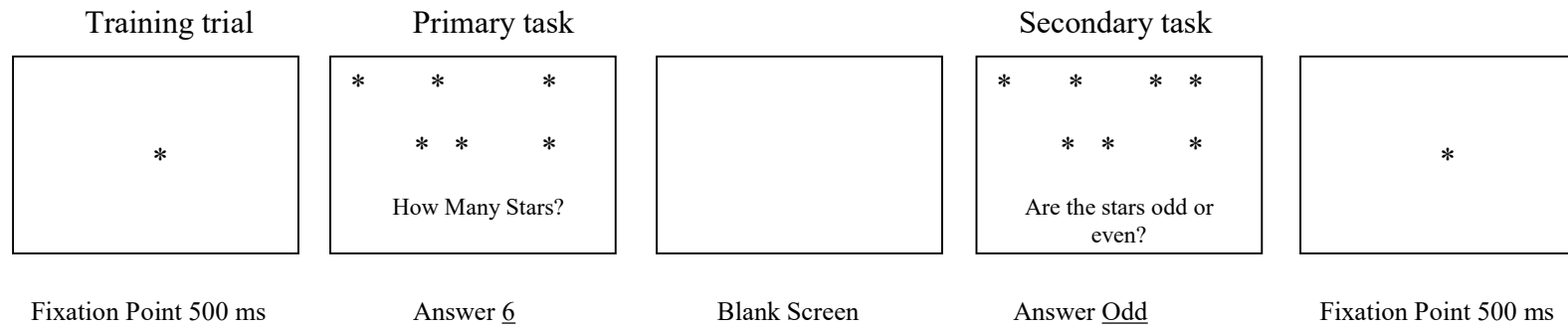
**Figure 3: Example configurations of primary task and secondary task during training.**

| Transfer trial | Primary task | | Secondary task | |
|---|---|---|---|---|
| | *    *    * *<br><br>*  * * *<br><br>How Many Stars? | | *      *  *<br><br>*  * *<br><br>Are the stars odd or even? | |
| * | | | | * |
| Fixation Point 500 ms | Answer 8 | Blank Screen | Answer Even | Fixation Point 500 ms |
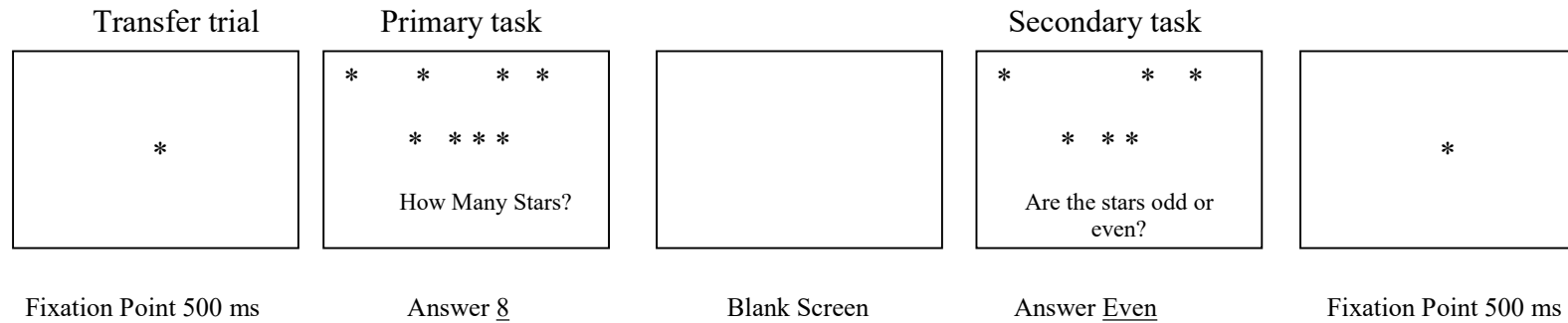
**Figure 4: Example transfer configurations of the primary task and secondary task.**

Each configuration in the primary task was presented 100 times. Lassaline and Logan (1993) found automaticity occurred in as little as 45 minutes of training over four training sessions, with each level of numerosity being presented four times in each of four 120-trial blocks, for a total of 16 presentations per item. Therefore, 100 numerosity presentations were expected to sufficiently facilitate automaticity. In the transfer trials, the secondary task stimuli were altered. Participants were assigned to one of three conditions, control, B1 or B2. In the control condition no change was made to the stimuli in transfer trials. So, all aspects of the primary and secondary tasks were the same in the training and transfer phases. The experimental group B1 had asterisks added during training and subtracted during transfer trials. Group B2 had asterisks subtracted during training and added during transfer. RT and error rate was examined for the primary task of each trial to determine the effect of the change to the secondary task in transfer on primary task performance. It was hypothesised that a change to the secondary task may reflect whether automatic skills from the primary task are affected by a context change in the secondary task. In other words, an increase in RT on the primary task might suggest that automatic skills used to perform the primary task can be affected by novel context changes (i.e., changes to the secondary task). Conversely, if RT on the primary task continues in accordance with performance observed in training, this would indicate that automaticity is stable and adaptable to context changes.

**Predictions based on the research and theories.**

There are three possible generalisations for how automaticity and transfer could be connected:

1. Transfer of an automated skill can be expected if the training task and the transfer task are exactly the same but only time has elapsed between performance of the two tasks.

2. Zero transfer of an automated skill is expected if the training task is different to the transfer task, that is, the skills used in the training task are of little or no use in the transfer task due to differing task requirements, strategies, or task goals. Any change to transfer performance will result in performance returning to a pre-training level.

3. Partial transfer is expected if both the training and transfer tasks are the same, however, something regarding the nature of the task is altered or something surrounding the task is altered. That is the task remains the same between training and transfer, but the context is manipulated; therefore, the same task requirements, strategies and task goals remain; hence, performance should be maintained (Anderson, 1982). However, as demonstrated in research reported by Speelman and Kirsner (2001), Speelman et al. (2011), and Speelman and Parkinson (2012) transfer is not occurring as would be predicted by theories of skill acquisition and transfer. This leaves to question what the best learning situation would be; to apply automatic recall of facts, or flexible knowledge?

There is a gap in the current literature of the role of automaticity in skill acquisition and transfer. Although automaticity is the result of skill acquisition, there is debate as to how automaticity may affect subsequent learning, there is also a lack of a central definition for automatic behaviour that is applicable in both experimental conditions and everyday learning contexts.
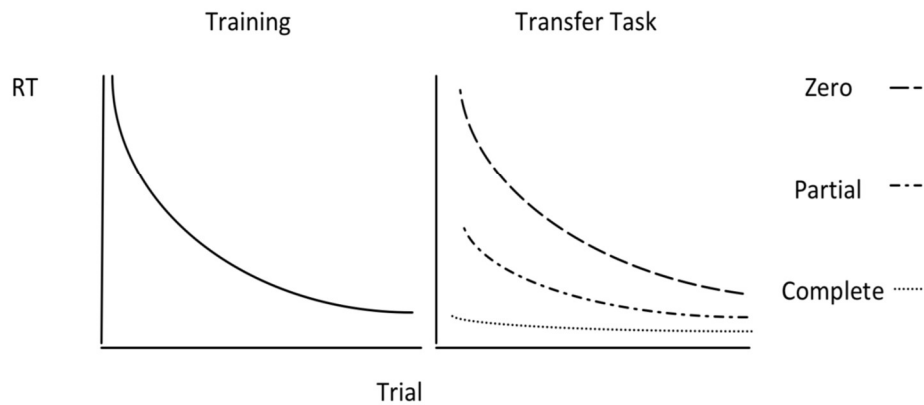
**Figure 5: Possible scenarios of transfer after an initial training phase based on RT and number of trials.**

Positive complete transfer has been demonstrated by research, such as Singley and Anderson (1989) who suggest that the amount of production (or skills) overlap is responsible for the amount of transfer predicted (see Figure 5). However, previous studies (i.e. Speelman & Kirsner, 1993) found that prediction of transfer performance based on production overlap is not reliable as performance under conditions of complete production overlap does become disrupted with context changes resulting in partial transfer.

It was predicted that transfer performance of the primary task in experiment one would reflect one of the following possible scenarios (Figure 6).
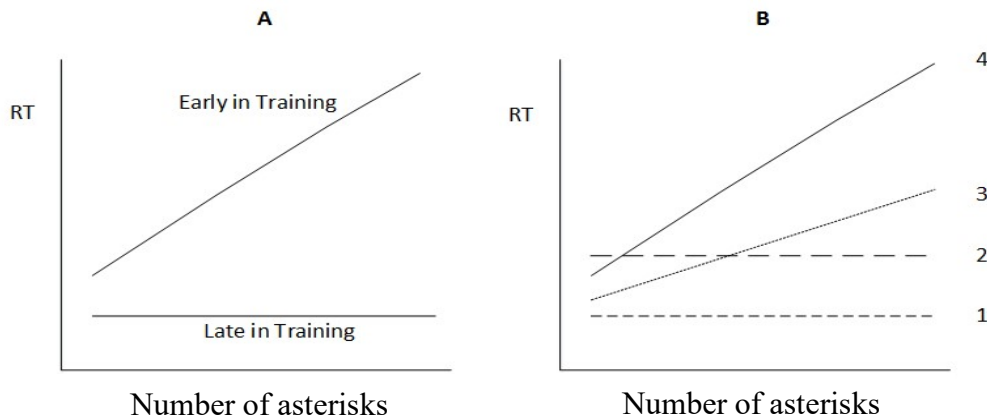
**Figure 6: Transfer predictions for RT as a function of the number of items in each stimulus.**

A refers to the typical performance patterns demonstrated in early and late training based on theoretical explanations. B refers to possible transfer scenarios (1, 2, 3, 4) based on Lassaline and Loogan's (1994) findings.

Scenario one: Transfer RT will be unaffected by the number of asterisks in the picture. Thus, there will have been complete transfer of automaticity, supporting the ACT theory where transfer is governed by the amount of production overlap and the dual processing theory (Schneider & Shiffrin, 1977) of automated task components. In addition, such findings would support Logan's instance theory of automaticity where tasks that have been experienced before may become automated and thus, reliably retrieved from long-term memory in a fast and efficient manner due to the development and refinement of an episodic trace that is undisrupted by contextual change.

Scenario two: Transfer RT may increase but remains unrelated to the number of stars. Thus, automaticity and transfer are independent: automaticity is retained (i.e., RT is unrelated to the number of asterisks), but only partial transfer is observed (i.e., Transfer RT is slower than final Training RT). The change in task conditions imposes an overhead in performance,

as suggested by Speelman and Kirsner's (2001) research, where any change to the transfer task provoked a reconceptualisation of what is required to complete the task.

Scenario three: Transfer RT may increase as the number of stars increase, but at some fraction of the rate observed during early training. That is, performance is not quite at early training levels but somewhere between early and late in training. This would imply that changes to the secondary task somehow reduce the extent of automaticity of performance on the primary task. Such a result would not support or falsify Logan or Anderson's predictions, but it would imply that any change to task conditions can result in some loss of automaticity due to participants' reconceptualisation of the overall task environment, even if the specific task itself has not changed.

Scenario four: Transfer RT returns to pre-training times where RT is a function of the number of stars displayed. Thus, automaticity is lost when the task conditions change, and no transfer occurs. This result would falsify both Logan and Anderson's predictions of automatic behaviour where practice and instance exposure allows transfer of automatic skills.

If performance followed scenario two, and RT performance recovers after an initial disruption and continues to decrease as the number of trials increase, both the ACT and instance theories would be contradicted. Nevertheless, learning to automaticity would appear to benefit overall learning, or at least would not be considered a hindrance to learning despite the task reconceptualisation. Conversely, if RT did not recover after the initial disruption, supporting either scenario three or four, it would appear that automaticity is lost due to contextual changes. This may discredit the notion of waiting for automaticity to be achieved before moving on in complexity, as automatic performance may not be transferred to a new context.

There is debate as to whether or not skill transfer is possible with automatic behaviour. Some researchers (e.g., Anderson, 1987) suggest that transfer is dependent on the amount of component overlap between the training and the transfer tasks, whilst others (e.g., Logan, 1988; Schneider & Shiffrin, 1977) postulate that learning is an accumulation of consistent instances, and so transfer is not possible if that particular context has never been encountered. However, based on theories of skill acquisition (e.g., ACT theory, Anderson, 1987) and theories of automaticity (e.g., instance theory, Logan, 1988) it is suggested that if a training task and a transfer task share similar components but the transfer task represents an altered form of the training task, skill transfer should be observed despite the establishment of automaticity. This however, as reported by Speelman et al. (2011), Speelman and Kirsner (2001), and Speelman and Parkinson (2012) does not seem to be the case.

## Method

### Participants.

Thirty-two psychology students from Edith Cowan University voluntarily participated in the study. Participants were recruited via the ECU Cognition Research Group Participant Register. The inclusion criteria required participants to have 'corrected' or 'corrected-to-normal' vision and English as their primary language. The participants' ages ranged from 17 to 65 years. Participants were reimbursed with a $20 shopping voucher for their time.

### Design.

The experiment was divided into two phases: training and transfer. In both phases, each trial had two parts, a primary and a secondary task. In both phases of the experiment, the nature of the primary task was identical. That is, a number of asterisks were presented on the screen, and participants were required to indicate the number of asterisks that were displayed. After a participant had given their response to the primary task of the trial, the secondary task

was immediately initiated. The secondary task of each trial had two versions. One version of the secondary task was presented in training trials, and the other was presented in transfer trials. The order of which version was presented differed according to the assigned condition (B1 or B2; A third, control, condition only utilised one version throughout training and transfer trials and is explained in more detail below). In one version, the configuration of asterisks that had been presented in the primary task was presented again, but with additional asterisks on the screen. The participant was then required to indicate whether the new number of asterisks was odd or even. In the other version, the configuration of asterisks that was presented in the primary task was presented again, but with a number of asterisks removed from the screen.

During training trials configurations of six, seven, eight, nine, 10, and 11 asterisks were presented in the primary task, 100 times each. During transfer trials the same six asterisk configurations were presented 50 times each. Participants were separated into one of three groups. Group A (control) where both the tasks in training and transfer trials were the same (i.e., there was no change in any of the tasks). The control group experienced the same context in the primary task so that asterisks were added to the configuration in the training secondary task, and were also added in the transfer secondary task. For groups B1 and B2 (experimental groups) the nature of the task during training and transfer was altered so that, for counterbalancing purposes, the experimental group B1 had asterisks added during training and subtracted during transfer trials. Group B2 had asterisks subtracted during training and added during transfer (see Figures 7 and 8).

*

        *

           *                 *

       *

               *

How many asterisks?
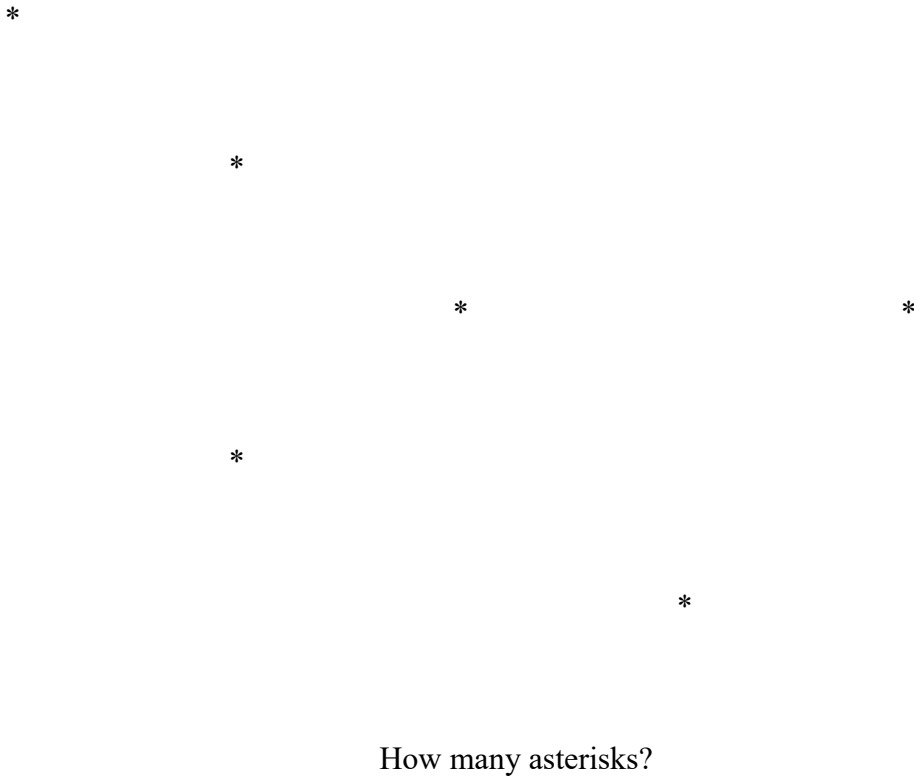
**Figure 7: Primary task of a trial in experiment one.**

  *             *

      *

           *                *

      *

  *                *

Is the number of asterisks odd or even?
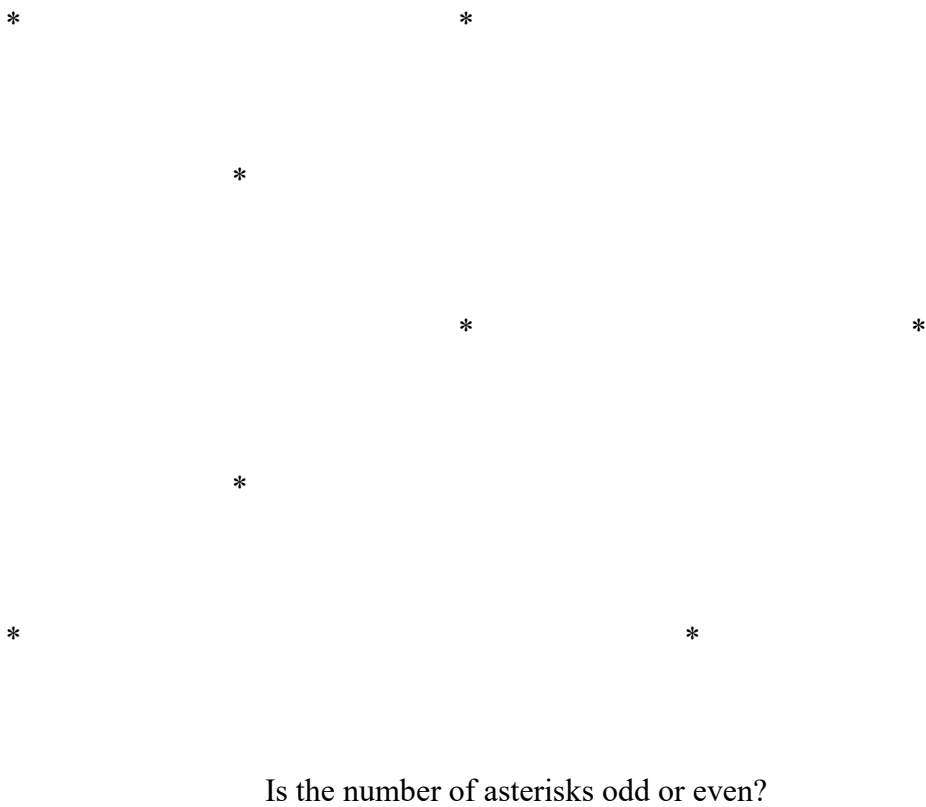
**Figure 8: Secondary task of a trial in experiment one.**

**Apparatus and stimuli.**

The experimental design involved a two-part task being presented in a training phase (total 90 mins) and a transfer phase (45 mins). During both phases, the primary task of each trial involved a configuration of asterisks, ranging in number from six to 11, being presented in the centre of a computer screen. In the training phase, the secondary task of each trial required participants to answer whether the number of asterisks was odd or even. Asterisks were either added or subtracted from the primary task configuration depending on the assigned condition. The first session comprised of 100 presentations of each configuration of the primary task (100 x 6 = total 600 trials), and the second session comprised of 50 presentations of each configuration (50 x 6 = total 300 trials). Each trial of training and transfer had a matched secondary task configuration. Table 1 lists the level of numerosity with the number of asterisks added or subtracted in accordance with the group allocation (A, B1 or B2). Each configuration had two associated secondary task configurations within a particular phase, one of which was an odd number of asterisks and the other an even number. In this way, a participant could not predict the correct answer in the secondary task just from the configuration in the primary task.

Each asterisk was separated from other asterisks within a stimulus configuration by at least 1 cm vertically and horizontally. Dell personal computers were used to display the stimulus patterns, and a SuperLab (RB-840) response pad was utilised by students to report the number of asterisks presented in the primary task of the task. There were six keys on the response pad, marked six, seven, eight, nine, 10, and 11. In the secondary task participants were required to indicate whether the number of asterisks displayed was 'odd' or 'even'. The response pad had two additional keys marked 'odd' and 'even' (see Appendix A).

**Table 1: Level of numerosity with corresponding asterisks for secondary task.**

| Level of numerosity in the primary task | Number of asterisks added in the secondary task | Number of asterisks subtracted in the secondary task |
| --- | --- | --- |
| Six | 1 | 3 |
| | 2 | 2 |
| Seven | 2 | 3 |
| | 1 | 2 |
| Eight | 2 | 1 |
| | 5 | 3 |
| Nine | 1 | 2 |
| | 1 | 1 |
| Ten | 1 | 2 |
| | 3 | 4 |
| Eleven | 1 | 1 |
| | 1 | 3 |

## Procedure

The research had approval from the ECU Human Research Ethics Committee. A suitable time was arranged with participants where the researcher verbally advised them of the rationale and merits of the research, asked if they had any questions, and invited them to participate. Participants were then provided with an information letter (Appendix B) and an informed consent form (Appendix C). The informed consent form reiterated that participation was voluntary and as such at any time they could withdraw from the study. The form also provided participants with another prompt to ask questions if there was anything they did not understand about the experiment.

A practice phase of 12 trials (1 block) allowed participants to familiarise themselves with the training procedure. The practice items were not presented again in the rest of the experiment. Once participants fully understood the procedure the training trials began. Participants were randomly assigned to one of three conditions: group A (control; $n = 12$), group B1 ($n = 7$) and group B2 ($n = 8$). Participants were instructed to rest their fingers on the buttons in preparation for the trial to begin. In the primary task of each trial, across all three conditions, a fixation point appeared in the centre of the screen for 500 ms, followed by a configuration of six to 11 asterisks arranged randomly around the screen. The pattern remained onscreen until a response was made on the response box by pressing one of the keys that were labelled with the possible number of asterisks (i.e., six to 11). A blank screen then followed for 250 ms. Another configuration of asterisks was then displayed. Participants were asked to determine whether the configuration consisted of an odd or even number of asterisks by pressing one of the corresponding keys on the response box labelled 'odd' and 'even'. Participants were instructed to respond as accurately and as quickly as possible to prevent guessing. Participants were given an optional break after 25 blocks. If a participant

answered incorrectly on a primary or secondary task, the trial was discontinued and a new trial began. The incorrect trial was presented at a later position within the same block.

## Results and Discussion

The present study set out to clarify the relationship between automaticity and skill acquisition and transfer. This involved two research questions:

1) To what extent are automaticity and transfer performance related? Specifically, how is RT on the primary task affected when task context changes are implemented in the transfer phase (i.e., changes are made to the secondary task)?

2) How much training is required to obtain the most successful transfer? Can some degree of automaticity lead to successful transfer? Specifically, is performance on the primary task slowed because of changes in the secondary task, or does primary task performance continue to improve according to power functions that describe training performance?

If positive transfer is observed (i.e., primary task RT in transfer is unaffected by changes in the secondary task of each trial) this will support the theoretical interpretations of the ACT (Anderson, 1982, 1987, 1992, 1993) and instance theories (Logan, 1988, 1990), suggesting once skills have become automatic, performance is unaffected by contextual changes. Conversely, if transfer is not successful and disruption is apparent (i.e., primary task RT is slowed during transfer trials), there would be reason to suggest that contextual changes result in a conceptual readjustment of the task causing participants to rethink what is required (Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2012).

The results of experiment one were analysed using Microsoft Excel 2010 and SPSS 22.0 Software for Windows to determine if there was a relationship between whether or not someone had attained automaticity on the counting task, and to examine the extent to which

their performance was affected by the change in task context created by changes in the secondary task of each trial.

**Reaction time.**

The average RT across all levels of numerosity for training and transfer blocks was calculated to investigate the pattern of learning and to enable visual inspection of the data for changes in RT after block 101: the transfer phase. Individual mean accuracy of 80% for the primary task of the visual numerosity task was required for data to be included in the RT analyses (Training: $M = 96.85\%$, $SD = 2.48$; Transfer: $M = 96.78\%$, $SD = 2.93$; Total: $M = 96.92\%$, $SD = 2.25$). Trials that were identified as exceeding the maximum RT cut-off point of 9000 ms were labelled as incorrect and were omitted from the analyses. The performances of five participants fell short of the accuracy and/or RT criteria for inclusions and so were omitted from the analysis.

Figures 9, 10, and 11 show the means for each block plotted along with a power function of the form $RT = a + bP^{-c}$ (where 'RT' is reaction time, and 'P' is the number of blocks, and 'a', 'b' and 'c' are performance parameters) that was fitted to the 100 blocks of training, and extrapolated for a further 50 blocks into the transfer phase. Asymptotes constrained to a minimum value of zero were utilised in the power functions.[1] Power functions provided a high degree of fit (high $r^2$ and low root mean squared deviation (rmsd) values) to the observed training RT in the control and experimental conditions, suggesting that performance was in accordance with the power law of learning (Newell & Rosenbloom, 1981).

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[1] When asymptotes were left free to vary, in all cases the resulting best-fit functions had negative asymptotes, which are psychologically implausible.
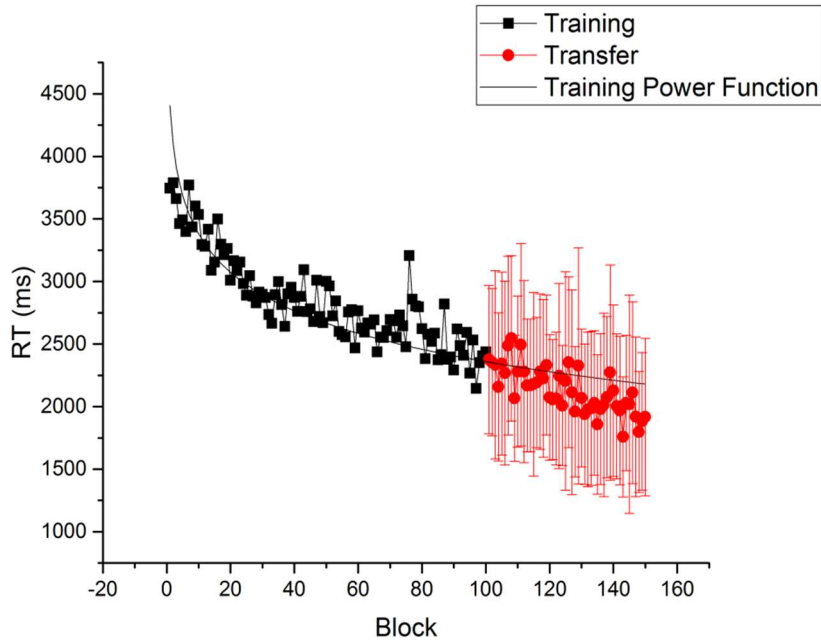
**Figure 9: Mean RT in the primary task of each trial for the control group.**

The smooth line is the power function that provided the best fit to the training phase data and was extrapolated to the transfer phase (RT = 0+4580.79*Block$^{-0.14}$ $r^2$ = .88, rmsd = 217.53). Error bars represent 95% confidence intervals.
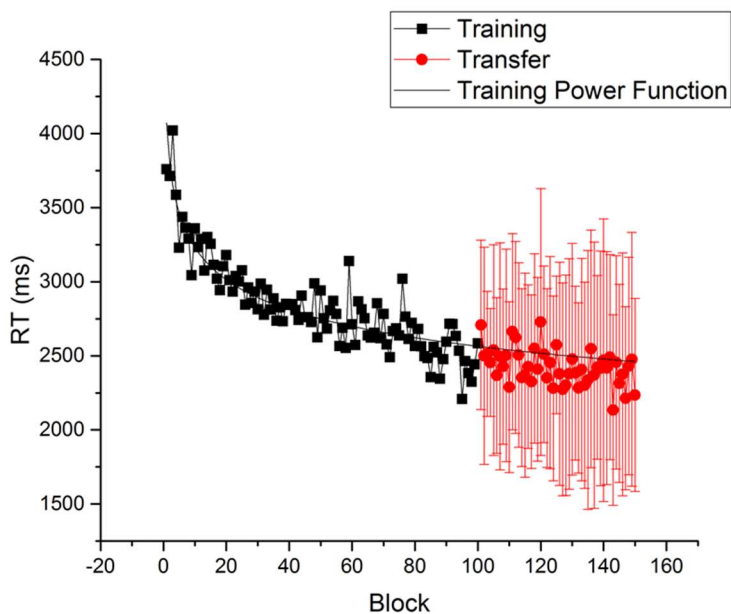


**Figure 10: Mean RT in the primary task of each trial for the experimental condition B1.**

The smooth line is the power function that provided the best fit to the training phase data and has been extrapolated to the transfer phase (RT = 0+4071.03*Block-0.10, r2 = .92, rmsd =135.83). Error bars represent 95% confidence intervals.
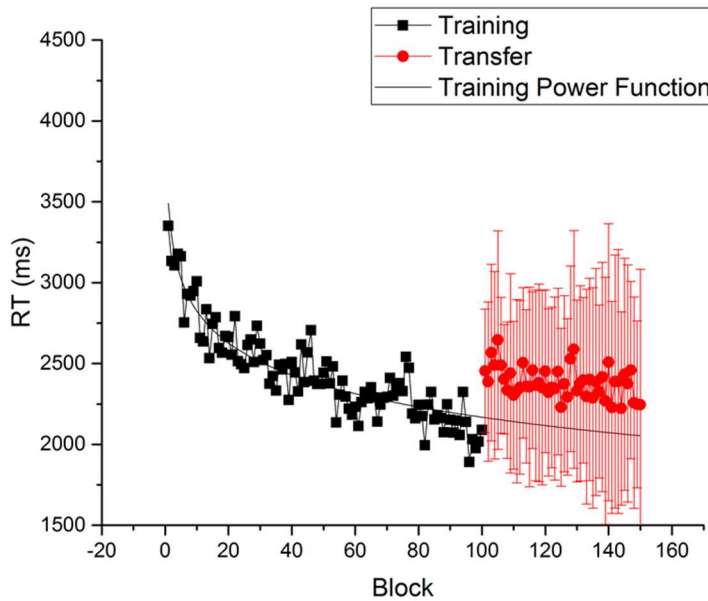
**Figure 11: Mean RT in the primary task of each trial for the experimental condition B2.**

The smooth line is the power function that provided the best fit to the training phase data and has been extrapolated to the transfer phase (RT = 0+3564.38*Block$^{-0.11}$, r$^2$ = .79, rmsd = 179.99). Error bars represent 95% confidence intervals.

**Disruption measure.**

To address whether there was a general effect on performance in the primary task caused by changes to the secondary task, three one-way repeated measures analysis of variances (ANOVA) were used to compare the mean primary task RT in the last block of training (A: $M$ = 2437.29, $SD$ = 873.58; B1: $M$ = 2583.68 ms, $SD$ = 202.86; B2: $M$ = 2089.48 ms, $SD$ = 226. 40) with the mean primary task RT in the first block of transfer (A: $M$ = 2376.5667, $SD$ = 932.82; B1: $M$ = 2708.95 ms, $SD$ = 233.40; B2: $M$ = 2454. 12, $SD$ = 161.60). The experimental conditions were analysed separately due to the profound differences in RT performance at the introduction of the new context. The ANOVA results of control condition A indicate, as expected, RT did not significantly increase between blocks 100 and 101. RT in experimental condition B1 did not significantly differ between training and transfer blocks ($p$ < .05). Although average performance of the primary task in the first

block of transfer appears to be slower following the change in task context, this change in RT did not significantly differ from RT observed at the end of training. Experimental condition B2 however, did show a statistically different RT performance between training and transfer blocks $F(1,7) = 12.02$, $p = .01$. Average performance of the primary task in the first block of transfer appears to be substantially slower than in the last block of training.

Speelman and Kirsner (1997) suggest that transfer performance may be predicted by extrapolating power functions that describe training performance. Therefore, to assess the extent to which transfer performance could be predicted from training performance, the power functions derived from the training phase data were extrapolated a further 50 blocks and compared with observed transfer RTs in the experimental conditions (see Figures 9, 10, and 11). Transfer performance is considered to be predicted well on the basis of training performance where extrapolated values pass within the 95% confidence intervals of the transfer RTs (Speelman & Kirsner, 2001). As expected, the control group demonstrate no change in transfer phase, and predicted RT values all pass within the 95% confidence intervals. RT in the transfer phase appears to be faster than the predicted values and RT improves with the increase in trials. For group B1, although RT appears to be slowing down in the first block of transfer compared to the last block of training for group B1, this was not by a statistically significant amount (see Figure 10). Furthermore, RT in transfer appears to be generally faster than the predicted RT. The transfer results for group B1 indicate that after an initial slowing of RT after the context change to secondary task, subsequent RT appears to be unaffected. Group B2 results appear to demonstrate a large slowing in RT performance in transfer, further suggesting that training performance may be affected by the context change to secondary task (see Figure 10). However, due to the large span of confidence intervals the extrapolated values all pass within the 95% confidence intervals of transfer RTs; therefore this difference is not considered to be significant. Group B2 transfer results indicate that

performance is affected by the context change, however due to the substantial variation of individual performance reflected in the confidence intervals this difference was not statistically significant.

To further examine whether transfer performance is maintained after the initial readjustment in the first block of transfer, a repeated measures ANOVA was conducted on the first four transfer blocks (i.e., blocks 101, 102, 103, and 104) for each of the experimental conditions and control condition. No significant main effect of transfer block was reported ($p > .05$).

The two experimental conditions appear to present differing transfer performance RT. Condition B2 demonstrates a different performance pattern compared to condition B1 with RT reflecting an almost reverse pattern than expected based on the ACT and instance theories. That is, if context changes to secondary task did not affect automatic skill performance of the primary task, a continuation of the typical learning curve would be demonstrated. However, B2 performance reflects a shift in performance that suggests a different strategy may be in use than the one participants employed in the training trials.

According to the ACT and instance theories complete positive transfer should occur under the conditions of this experiment, as the primary task numerosity configurations encountered in training are identical to those encountered in transfer. Although primary task RT appears to increase with the change to the secondary task in condition B1, the increase between blocks 100 and 101 was not statistically significant, and therefore may be explained by scenario one (see predicted scenarios p. 87-88 of this thesis), which predicts complete skill transfer. Anderson's ACT theory (1993) and Logan's instance theory (1988) predictions seem to support the aforementioned results. Conversely, Figure 11 indicates a marked disruption on transfer block 101 for condition B2, consistent with scenario four. The results reveal that transfer performance for this group was significantly disrupted. This supports the

results obtained by Speelman and Johnson (2012) and Speelman and colleagues (i.e., Speelman et al., 2011; Speelman & Kirsner, 2001). However, performance in block 101 was not as slow as performance times demonstrated in the first block of training, therefore, partial transfer may be suggested, supporting scenario three (see p. 83 of this thesis).

Performance in both experimental conditions indicated partial transfer following context changes. After the initial increase in RT with the context change, training performance appears to recover in subsequent trials. Condition B2 performance also suggests some loss of the automaticity of training performance, with transfer RT remaining slower than training RT, after the context change is introduced. Speelman and Parkinson (2012) suggest that a mental set representation is held in working memory to aid efficient task performance. When a transfer disruption is observed, this may indicate that a set of production rules, which were used in the training task, are no longer effective in a new transfer environment. That is, the set of processing rules, which were developed to perform the primary task of each trial in training, cannot be used in transfer; therefore a reassessment of the task is required. Further to this, Healy et al. (2005) suggest that a two-step task design may be interpreted as a single functional task. Although the two tasks are presented and intended to be two separate tasks they are interpreted and learned by association as one task. Any change to the secondary task of the task is interpreted as a change to the whole task, thereby causing reconsideration of the task requirements in future trials. In the current experiment the two parts of the task may not be easily distinguishable and serial association may be facilitated. In order to determine more effectively how context changes affect automatic performance, a more discrete separation of parts one and two of the experimental task was implemented in the design of experiments two and three.

Figures 11 and 10 indicate differences in disruption (or readjustment) impact of automatic skill performance with context changes. This suggests that participants' conceptualisation of the context change may have differed according to experimental condition. What was intended as a counterbalancing measure may in fact reveal differences in task difficulty in the design of conditions B1 and B2. Speelman and Kirsner (2001) suggest that an increase in complexity leads to greater disruption than a decrease in complexity. It could be then that the context change of subtraction to addition in condition B2 might represent an increase in complexity. Speelman and Kirsner found that, despite a conceptualisation readjustment, performance continued to improve in accordance with training performance, and so performance returned to predicted levels. However, the current experiment revealed that performance improvements during transfer were disrupted in condition B2. In the more complex task condition participants may have been questioning the requirements of both the primary and secondary tasks and continued to do so throughout the transfer trials. The differences in complexity in combination with the nature of the two-step serial design may be responsible for the differences in disruption impact.

**Individual performance.**

It was suggested in Chapter 3 that participant characteristics, such as motivation, performance pressure and learning styles, could have an impact upon skill acquisition and performance.

Figures 12, 13, and 14 present each participant's RT on the primary task of each trial, for all blocks in the experiment. The control condition (see Figure 12) indicates an overall expected pattern of improvement, with the exception of two participants. Participant 22 demonstrated highly varied RT block performance and participant 25's RTs almost appear to increase throughout training.

In the experimental conditions, where the secondary task was changed from addition to subtraction, participants demonstrated a typical pattern of RT improvement with extended practice that has already been highlighted in the group average RT (Anderson, 1992, 1993). In condition B1 (see Figure 13) the secondary task was changed from addition to subtraction. No disruption was demonstrated when context changes were implemented in block 101. Participants one and four display data with greater variation in RT compared to the group average, however the overall trend from all participants and the group average suggests results that could be considered similar to classic learning curves. This suggests that participants may be uniform in their approach to the task and there is an overall slowing in performance gains in later blocks, which is in line with the power law of learning data. Both the control and B1 conditions demonstrate a similar pattern of improvement throughout training.

Figure 14 shows variance in RT performance over the training trials. Specifically, participants eight, 12, and 14 demonstrate a general improvement in RT performance with an increase in RT in the transfer phase of block 101. Participants nine, 10 and 11 demonstrate performance that remains similar to RT performance displayed in training. That is, there appears to be no sudden increase or decrease in performance over time. However, participant 15 appears to demonstrate improvement in RT over practice, with a slight increase in RT at block 101, yet performance continues to decrease in a similar manner observed in training.
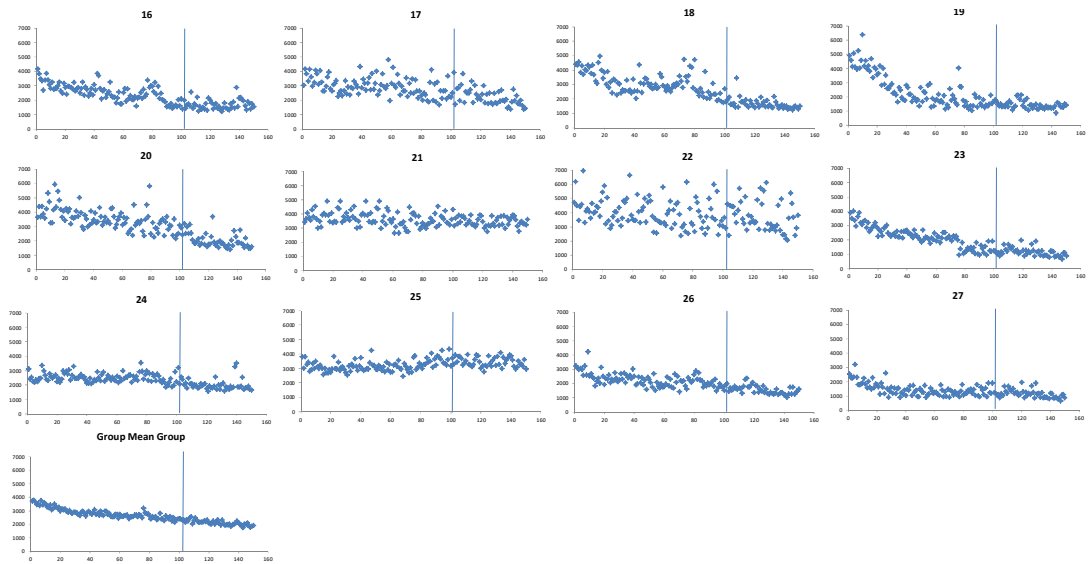
**Figure 12: Individual mean RT performance data for 13 participants in the control condition. The figures represent RT (ms) as a function of practice (block)**
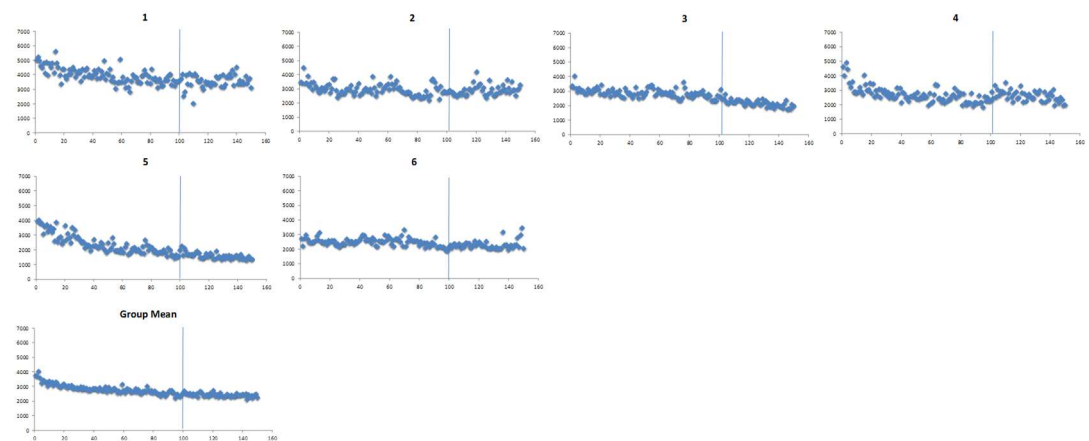


**Figure 13: Individual RT performance data for seven participants in experimental condition B1 and mean RT performance data for the primary task of each trial. The figures represent RT (ms) as a function of practice (block)**
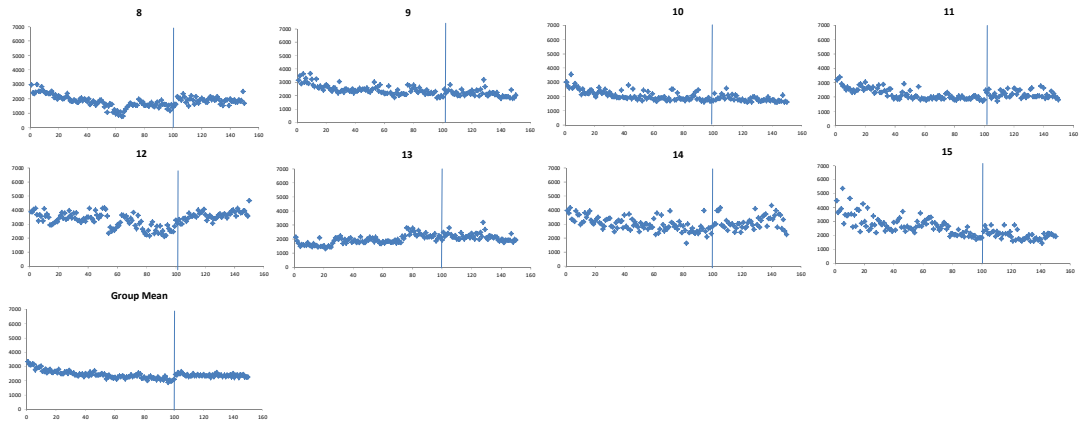
**Figure 14: Individual RT performance data for seven participants in experimental condition B2 and mean RT performance data for the primary task of each trial. The figures represent RT (ms) as a function of practice (block)**

## Automaticity

Average group RT early in training is dependent on the number of items presented on screen. The slope of linear regression relating response latency to numerosity was calculated across three phases of training (blocks 1–10 early, 50–60 mid, 90–100 late) to determine if and when automaticity was reached. Regression lines of the form RT = a + b*numerosity were fitted to the data for each person in each of the three training phases. The slope values for these lines are presented in Table 2. Mean RT for each level of numerosity for each phase is presented in Figures 15, 16, and 17, which demonstrates that RT in the early phase of training increased as the number of items of screen increased. RT decreased in mid training blocks so that the slope of regression was less inclined than early training blocks. RT was almost independent of numerosity in the late training phase, with only a slight increase in RT with the increase in numerosity. This pattern of performance appears to be consistent across both experimental conditions and the control condition and is consistent with other research in the development of automaticity in the visual numerosity task (Logan, 1988). Transfer performance however differs between the experimental conditions.

As demonstrated in Figures 15, 16, and 17 all conditions demonstrate performance in accordance with the typical development of automaticity (Chi & Klahr, 1975; Lassaline &

Logan, 1993; Logan, 1988). That is, by the late training phase RT performance appears to be independent of numerosity. Group B1 shows that transfer performance appears to be unaffected by context changes with performance remaining independent of numerosity. Group B2 however, showed an increase in RT with numerosity, with performance demonstrating support for scenarios three and four (see page 87-88). During transfer, RT as a function of numerosity increased at some fraction of the rate observed in early training performance. This suggests some loss of automaticity. Due to the difference in complexity between the experimental conditions neither Anderson (1982, 1987, 1992, 1993) nor Logan's theory (1988, 1990) can be falsified or supported. One change in context appears to represent an increase in complexity; the other represented a decrease in complexity.

The results can be interpreted in a number of ways. The results of group B1 would appear to support the inferences from the ACT theory where transfer is governed by the amount of production overlap (Schneider & Shiffrin, 1977). That is, as the configurations in the primary task in training are the same in transfer the same productions and rules apply, there is no need to resort to counting methods as the primary task remains unchanged. Such findings also may support Logan's instance theory of automaticity where tasks that have been experienced before may become automated and thus, reliably retrieved from long-term memory in a fast and efficient manner. Conversely, group B2 demonstrated an increase in the slope of the line that related RT with numerosity, with the slope sitting between the value that was observed in the mid and late training phases, consistent with the predictions of scenarios three and four, where RT has increased initially at some fraction of the rate observed in early training performance. This may indicate that in transfer, participants are relying on counting strategies rather than memory for the configurations. As the number of items on the screen in condition B2 increased from the primary task to the secondary task, participants may have resorted back to counting all configurations. The increase in complexity of the secondary task

would cause the participants to resort back to inefficient and non-automatic strategies. This may suggest the existence of an overhead in performance, as suggested by Speelman and Kirsner (2001), provoked by a reconceptualisation of task requirements. This suggests that theoretical interpretations of Logan (1988) and Anderson's (1992) theories regarding the transfer to automatic skills may be falsified; the change in task conditions did result in some loss of automaticity even though the task itself was not changed.

The variation in transfer performance between the experimental conditions suggests that the different changes to the secondary task affected transfer performance in the primary task differently. One change appears to represent an increase in complexity, the other represented a decrease in complexity. As the subtraction condition had fewer items on screen, participants in group B1 may have subitized numerosities (Chi & Klahr, 1975), and become faster at doing so, resulting in quicker retrieval strategies and representing a less complex task which is easier to automatise. However, it is important to note that only in some cases (i.e., numerosities six and seven) would the subtraction condition be in the range usually associated with subitizing. What is apparent in the results is that context does appear to affect the automaticity and transfer of learned items for in condition B2 where items are added. Thus, complexity appears to mediate transfer, that is, the complexity of the transfer task determines the extent of transfer.
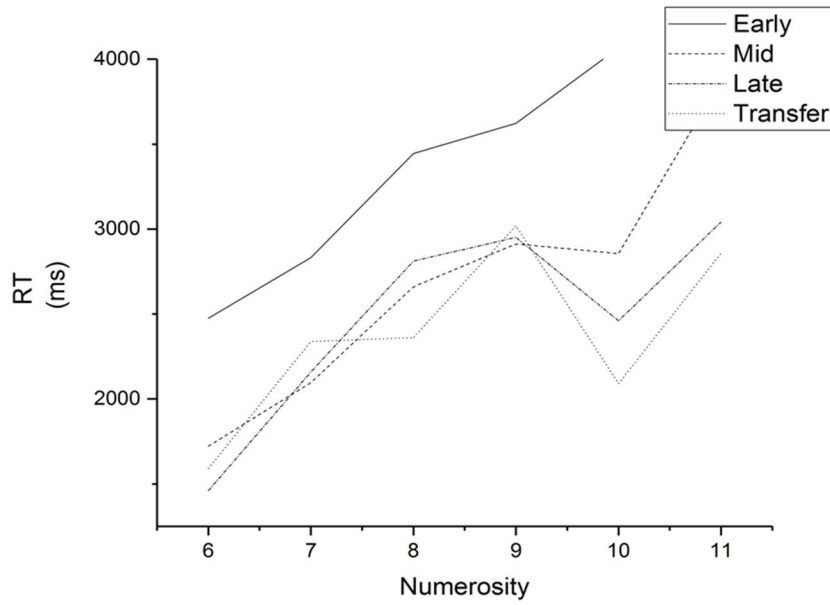
**Figure 15: Mean RT for the primary task of each trial as a function of numerosity for early, mid, and late training phases, and transfer in the control condition.**
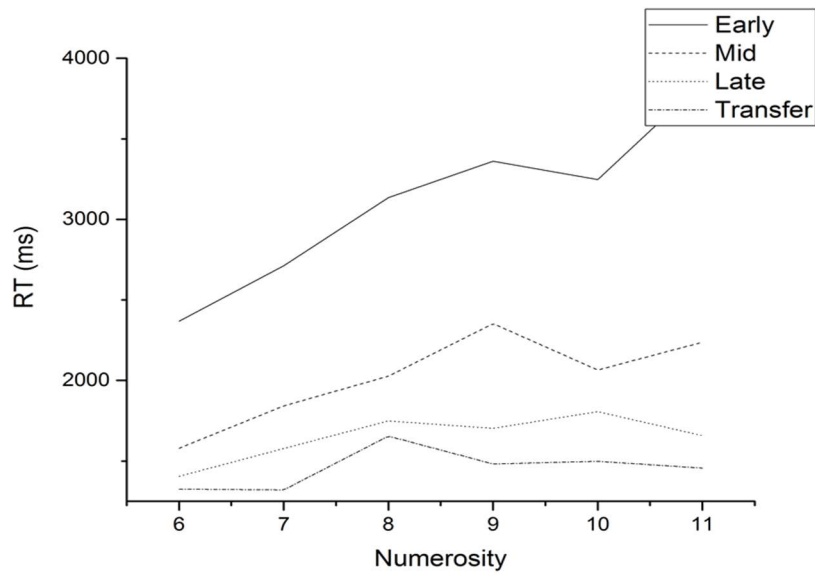


**Figure 16: Mean RT for the primary task of each trial as a function of numerosity for early, mid, and late training phases, and transfer in condition B1.**
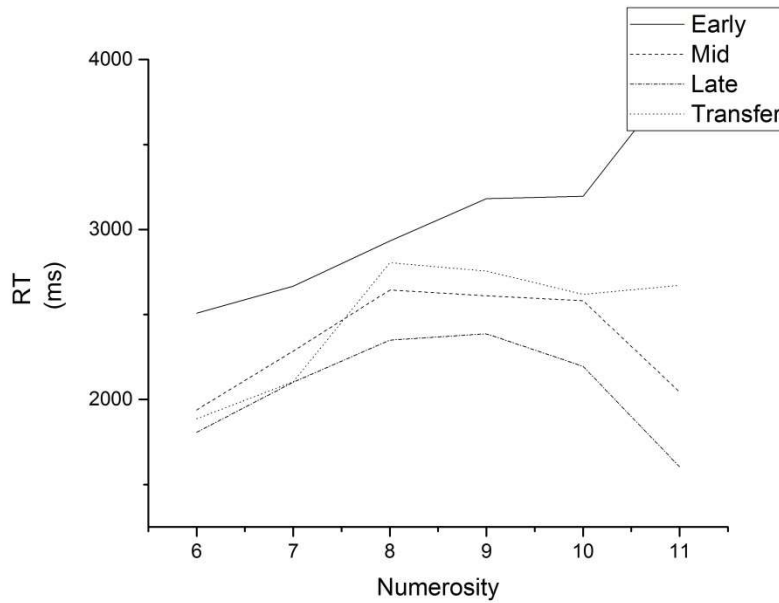
**Figure 17: Mean RT for the primary task of each trial as a function of numerosity for early, mid, and late training phases, and transfer in condition B2.**

The number of subjects whose regression slope values followed the pattern of the slopes calculated on group data was determined. Participants were classified as having achieved automaticity using two criteria:

*Criterion one.* This criterion of automaticity was a conservative approach based on Lassaline and Logan's (1993) findings, that automatic performance was achieved when the slope of the regression line relating RT to numerosity was less than or equal to 100 ms by late training phases.

*Criterion two.* The second criterion required an overall reduction in the slope of regression lines from early to late phases. That is, any decrease in the slope of regression lines for RT performance between early and late phases was considered to be approaching automaticity.

The coefficient of determination, $r^2$, was utilised to determine how well the data was fit by a straight regression line. It can be noted from Table 2 that participants who were automatic (according to criterion one) by the late training phase obtained low $r^2$ values. As $r^2$ explains how much variance is attributed to the variability of the response data around the mean, $r^2$ values are expected to be large, demonstrating a good fit between the predicted and observed slope of linear regression, for large regression slope values. Conversely, $r^2$ values are expected to be small for linear regression slope estimates that are close to reaching asymptote (i.e., zero). This would result from RT values for each numerosity value being roughly equivalent (i.e., very little variance) such as would be expected if participants had undergone a shift from rule based processing to memory retrieval.

There appears to be an inconsistency in $r^2$ values obtained by participants who had large slope values. A decline in standard deviation with task practice is expected to reflect consistent information processing (Ackerman, 1988). In this sample however, there appears to be a number of participants who did not demonstrate a reduction in standard deviation values, suggesting that task performance strategies may have remained inconsistent and varied throughout training. In the current results, it can be noted that whilst some participants approached automaticity, there appear to have been some people who did not. Whilst the group results suggest a shift to automatic performance, this was not a consistent finding amongst all participants. Some participants were not attaining automaticity, a finding that has not been reported widely in the literature. For example, in condition B1 43% of participants did not demonstrate a decrease in slope values indicative of approaching automaticity, whilst in condition B2 13 % also did not demonstrate this shift towards automaticity, and in the control condition (A) 30% failed to approach automaticity after extended practice.

**Table 2: Participant slope of regression lines fitted to RT data as a function of numerosity.**

| Participant | Group | Early slope | SD | Mid slope | SD | Late slope | SD | Transfer slope | SD | Measure of Disruption | Criterion 1 automaticity achieved (< 100 ms) | Criterion 2 automaticity achieved (reduction of slope from early to late)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | B1 | 453.78(.62) | 709.14 | 439.4(.12) | 419.60 | 380.27(.54) | 968.86 | 169.69(.55) | 517.97 | 116.33 | 2 | 1 |
| 2 | B1 | 249.87(.92) | 489.33 | 280.3(.67) | 637.95 | 171.82(.23) | 606.30 | 130.94(.15) | 635.35 | 89.33 | 2 | 1 |
| 3 | B1 | 379.52(.92) | 739.41 | 403.78(.76) | 869.53 | 356.1 (.86) | 717.93 | 200.05(.81) | 415.65 | 466.17 | 2 | 2 |
| 4 | B1 | 616.36(.79) | 1297.87 | 299.15(.49) | 798.81 | 429.78(.83) | 884.48 | -24.99(.02) | 340.03 | 597.27 | 2 | 2 |
| 5 | B1 | 238.55(.42) | 689.98 | 106.63(.19) | 459.37 | 134.8(.62) | 319.39 | 34.98(.12) | 199.19 | 290.5 | 2 | 1 |
| 6 | B1 | 272.82(.99) | 512.83 | 328.32(.84) | 670.15 | 219.16(.75) | 472.61 | 199.15(.87) | 399.78 | 125.17 | 2 | 1 |
| 7 | B1 | 347.55(.92) | 679.56 | 288.36(.82) | 595.96 | 455.11(.91) | 893.65 | 186.02(.35) | 584.84 | -807.83 | 2 | 2 |
| 8 | B2 | 235.23(.96) | 449.20 | -35.36(.02) | 499.22 | 10.03(.00) | 339.44 | 235.09(.92) | 459.84 | 311.43 | 1 | 1 |

| Participant | Group | Early slope | SD | Mid slope | SD | Late slope | SD | Transfer slope | SD | Measure of Disruption | Criterion 1 automaticity achieved (< 100 ms) | Criterion 2 automaticity achieved (reduction of slope from early to late)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | B2 | 238.09(.91) | 467.42 | 245.26(.80) | 515.90 | 127.55(.68) | 290.32 | 188.45(.75) | 406.52 | 562.5 | 2 | 1 |
| 10 | B2 | 225.81(.82) | 466.12 | -69.77(.10) | 407.54 | -141.03(.33) | 460.99 | 4.47(.00) | 374.36 | 515.33 | 1 | 1 |
| 11 | B2 | 326.3(.71) | 726.65 | 22.58 (.02) | 317.34 | -40.65(.03) | 423.55 | 96.86(.20) | 405.62 | 688.83 | 1 | 1 |
| 12 | B2 | 296.25(.88) | 591.96 | -94.715) | 451.36 | -139.39(.27) | 502.45 | 213.38(.67) | 487.24 | -232.33 | 1 | 1 |
| 13 | B2 | -28.65(.03) | 334.43 | 194.02(.92) | 377.84 | 146.36(.64) | 343.38 | 188.45(.75) | 406.52 | 537.5 | 3 | 2 |
| 14 | B2 | 246.2(.51) | 648.05 | 96.12(.06) | 724.99 | -79.43(.05) | 657.82 | 159.78(.06) | 1178.14 | 162.33 | 1 | 1 |
| 15 | B2 | 495.33(.03) | 334.43 | -42.06(.92) | 377.84 | -43.75(.64) | 343.38 | 178.87(.75) | 406.52 | 451.17 | 1 | 1 |
| 16 | A | 441.92(.86) | 890.76 | 75.41(.12) | 416.07 | 108.94(.34) | 347.292 | 97.77 | 453.68 | -685.87 | 2 | 1 |
| 17 | A | 393.19(.37) | 794.61 | 352.17(.35) | 1110.23 | 303.42 (.12) | 1271.50 | 305.77 | 1382.45 | 283.67 | 2 | 1 |
| 18 | A | 481.32(.68) | 1095.55 | 431.72(.90) | 851.59 | -18.23(.00) | 796.96 | -18.28 | 898.92 | -915.5 | 1 | 1 |

| Participant | Group | Early slope | SD | Mid slope | SD | Late slope | SD | Transfer slope | SD | Measure of Disruption | Criterion 1 automaticity achieved (< 100 ms) | Criterion 2 automaticity achieved (reduction of slope from early to late)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 19 | A | 681.97(.69) | 1539.14 | 69.67(.30) | 820.75 | 46.94(.02) | 718.16 | 9.94 | 692.75 | 131.83 | 1 | 1 |
| 20 | A | 242.02(.54) | 618.39 | 645.56(.78) | 1369.56 | 466.34(.64) | 1088.88 | 300.4 | 949.37 | -155.67 | 2 | 2 |
| 21 | A | 484.79(.85) | 1539.14 | 629.9(.83) | 820.75 | 53.00(.60) | 718.16 | 482.22 | 692.75 | -1176.5 | 1 | 1 |
| 22 | A | 693.19(.68) | 1575.10 | 514.89(.57) | 1273.42 | 240.11(.29) | 829.72 | 84.47 | 786.50 | 595.33 | 2 | 1 |
| 23 | A | 237.02(.58) | 583.67 | 329.56(.42) | 955.48 | 118.28(.30) | 406.88 | -10.13 | 363.51 | -19.5 | 2 | 1 |
| 24 | A | 191.96(.78) | 406.92 | 351.92(.91) | 684.22 | 121.07(.17) | 543.04 | 194.01 | 586.00 | 1003.17 | 2 | 2 |
| 25 | A | 371.73(.97) | 706.70 | 477.92(.95) | 917.19 | 509.96(.61) | 1224.15 | 454.65 | 1200.27 | 537.33 | 2 | 2 |
| 26 | A | 597.03(.58) | 1469.82 | 254.34(.66) | 588.02 | 289.91(.92) | 561.58 | 179.84 | 382.60 | 359.5 | 2 | 2 |
| 27 | A | 285.17(.65) | 664.37 | 76.67(.12) | 419.60 | 129.45(.30) | 448.35 | -32.62 | 371.73 | -686.5 | 2 | 1 |

*1 = automatic performance (i.e., slope <100 ms). 2 = non-automatic performance (i.e., slope >100 ms). 3 = automatic performance in the early training phase. **1= automatic performance (i.e., slope decreasing from early to late training phases). 2 = non-automatic performance.

## Disruption and transfer

A measure of disruption for the primary task of each trial was calculated by subtracting, for each participant, the mean RT in the first block of transfer from the mean RT in the last block of training. A positive number indicates that performance was disrupted with the change of conditions in the secondary task of a trial. Table 2 indicates that 13 out of 15 participants (86.67%) in the experimental conditions were disrupted in transfer performance; six (85.71%) participants in group B1, and seven (75%) participants in group B2 were disrupted.

A large percentage (86.67%) of participants demonstrated a slowing of RT performance in transfer and a moderate percentage (40.73%) of participants were classified as not automatic, (as indicated by automaticity criterion two) by the late training phase. To examine the relationship between automaticity and transfer, a correlational analysis was conducted between the measure of disruption of on the primary task and the linear regression slopes relating RT to numerosity for each of the training phases. No significant correlation was found.

**Relationship between automaticity and transfer.**

According to automaticity criterion one, all participants in condition B1 failed to achieve automaticity by late training. Participants eight and nine from group B2 were considered automatic, and participant 13 was considered automatic at the beginning of the task. These three participants were also disrupted in the transfer performance. Using automaticity criterion two, all participants, except for three, four, and seven, were considered automatic in group B1. All participants in group B2 were considered automatic. Participant 13 was classified as not automatic by the late training phase even though they demonstrated a negative slope performance in early training.

Condition B2 indicated the most number of participants obtaining slope performance values less than 100 ms (criterion one) suggesting that automaticity was obtained more often in this condition compared to group B1. Automaticity differences associated with condition suggest that the training conditions affected training performance and the development of automaticity. Thus, by trying to counterbalance possible order effects in presenting the addition and subtraction task, comparisons of performance disruption in transfer between the experimental conditions may not be warranted because they reflect quite different performance conditions.

## Conclusion

The findings of this experiment did not present a consistent picture of the relationship between automaticity and transfer across all conditions, however they do demonstrate the impact of the experiment design and perceived difficulty of the secondary task on performance. Another possible limitation to be considered in this experiment is the similarity of items presented in the primary and secondary tasks. Participants may not have been aware of the two-part nature of this task aiding the use of non-efficient memory strategies. That is, as both primary and secondary tasks required the same counting strategy of items on screen participants may have perceived each stimulus as a new stimulus presentation rather than the same configuration for numerosity 6–11 with a matched secondary task. Consequently, counting strategies may have been used throughout the duration of the experiment rather than the intended implementation of memory strategies in the primary task and counting strategies in the secondary task after a number of training trials.

Alternatively, the similarity of the primary and secondary tasks may have facilitated conceptualisation as one serial task. The similarity of the two sub-tasks may have contributed to the development of a mental set (Speelman & Parkinson, 2012) or representation of a

single task (Healy et al., 2005). Thus, the change to the secondary task may have resulted in a change in strategy from memory to counting for both parts—even though the primary task remained the same. Further to this, as suggested by Dishon-Berkovits and Algom (2000), an automatic response, such as reading in the Stroop task, may be manipulated by the relationship between the distractor task and the target item. Similarly, Labuschagne and Besner (2015) also found manipulability of the Stroop effect when changing spatial attention. Thus, an automatic skill, such as reading, in the Stroop effect may not demonstrate the failure of an automatic skill but the influence of experimental design, or a change in context. In the current experiment disruption in transfer performance may not reflect the disruption of an automatic skill but more the influence of experimental design. One explanation of the differences in performance between B1 and B2 could be due to a possible increase in complexity of switching from subtraction to addition impacting upon performance.

The influence of experimental design has been discovered in these results. In conclusion, differences in participant RT performance were found to be reflective of the assigned experimental condition. To avoid intergroup differences one experimental condition was utilised for all participants. Furthermore, a clearer separation between the primary and secondary tasks was established by implementing a redesign of the secondary task for experiments two and three.

**Introduction to Experiment Two**

The results of experiment one showed that automatic skills could be disrupted by novel context changes, with condition B2 demonstrating a significant slowing in performance with the transition from training to transfer. The initial transfer disruption observed in conditions B1 and B2 is similar to the findings of Speelman and colleagues (i.e., Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2012). B1 RT recovered quickly in subsequent transfer trials, in accordance with predicted RT based on training performance, suggesting no loss of automaticity occurred. However, group B2 performance demonstrated a different pattern of performance in transfer than expected. Since RT remained higher than predicted values, some loss of automaticity may have occurred. Overall, the findings across all conditions did not consistently demonstrate support of the predictions outlined in Chapter 5. As highlighted in Chapter 6, the counterbalancing that was a feature of the design of experiment one might have been responsible for the difference in performance between B1 and B2. That is, the counterbalancing may have resulted in a difference in the task conceptualisation of group B1 compared to B2.

On the basis of experiment one findings, it was concluded that design elements should be refined in future experiments. Accordingly, a number of changes were made to the design of experiment two in order to refine the experimental design:

- Experiment one demonstrated that the two-part nature of the task was not obvious to participants and may have caused them to utilise non-efficient strategies, such as counting, for the duration of the experiment. Thus, experiment two was designed to make it more likely that in the primary task of each trial participants would begin by counting asterisks and then gradually recognise asterisk patterns and remember the correct response. This design

feature involved encouraging them to use a different form of processing in the secondary task of each trial (i.e., perform an arithmetic operation compared to another configuration presentation that was utilised in experiment one). Thus, in the secondary task participants were required to perform an addition problem in training trials, and a subtraction problem in transfer trials, with a response in the form of the answer being odd or even.

- In experiment one, the slope of lines relating RT to numerosity were still high by the late training phase, suggesting that participants were not approaching automaticity as expected. To induce automaticity more quickly in experiment two, each stimulus configuration was displayed in a unique colour. The corresponding response keys were coloured in the same manner. It was expected that by matching the colour of the keys to the configurations the probability of attaining automaticity would be greater.

- Experiment one included 100 presentations of each level of numerosity. Logan and Klapp (1991) found automaticity in as little as one hour of training on six alphabet arithmetic equations. Therefore, with the numerosity task simplified in experiment two with the addition of coloured configurations, it was expected that automaticity would be attained in fewer trials than in experiment one. Therefore training was reduced to 50 blocks and transfer was reduced to 25 blocks.

The hypotheses tested in experiment one were also tested in experiment two. If RT was not disrupted with the transition from training to transfer trials, then context would appear to have no effect over automatic skills acquired in training. Alternatively, if a transfer disruption was apparent, this would indicate that when the primary task remains unchanged, changes to the secondary task affect the ability to perform the primary task automatically,

possibly through some conceptual readjustment whereby participants rethink the overall task requirements (Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2014). Performance after the initial few transfer trials was expected to indicate whether automaticity is beneficial or a hindrance to learning. If performance recovered and RT continued to decrease with practice, automaticity would appear to be beneficial to overall learning despite the initial task re-conceptualisation. However, if RT did not recover after the initial disruption during transfer, this would suggest that automaticity is lost due to contextual changes.

In addition to experiment two addressing possible experimental confounds in experiment one, the roles of other variables in the link between automaticity and skill transfer were considered. In experiment one, it was apparent that many participants were not approaching automaticity as might have been expected based on the research of Lassaline and Logan (1993), Logan and Klapp (1991), and others (Anderson & Lebiere, 1998; Logan, 1988; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). This raises a question as to whether there are identifiable characteristics of people that might be associated with the likelihood that they would develop automaticity, such as working memory ability (Engle, 2002; Gathercole, Alloway, Willis, & Adams, 2006). Another purpose of this experiment was to determine whether individual differences in working memory impact upon an individual's ability to automatise the primary task, and maintain primary task performance with changes to transfer trials. Participant attributes, such as working memory, might account for the rate of attaining automaticity and transfer performance.

Working memory is suggested to be a 'pure' measure of learning potential as it is not strongly influenced by prior experiences or education, but it does measure the capacity to retain information and therefore the potential to learn (Alloway et al., 2005). Recent research in education has focussed on discovering possible links between working memory ability and

academic progress, with claims that working memory is a better predictor of academic

success than IQ tests (Alloway & Alloway, 2010). Alloway and Alloway (2010) suggest that

poor working memory leads to failure in tasks that involve storing and processing

information. Impairments in working memory have negative consequences for learning and

academic progress (Gathercole & Alloway, 2006). Poor working memory may result in

disruption of early learning processes leading to subsequent learning difficulties. In other

words, working memory may be considered a bottleneck for learning which supports the

acquisition of skills and knowledge in various domains (Gathercole, 2004; Gathercole &

Alloway, 2006).

Working memory has been described as a limited capacity central executive system

that interacts with a set of passive store systems used for temporary storage of different

classes of information (Baddeley, 1996). Individual differences in working memory capacity

have been identified as contributing to the ability to inhibit irrelevant stimuli (Engle,

Tuholski, Laughlin, & Conway, 1999), the ability to direct attention (Kane, Conway,

Hambrick, & Engle, 2007), and self-discipline (Duckworth & Seligman, 2005). For example,

Nicolson and Fawcett (1990) suggest that children diagnosed with dyslexia have a deficit in

the acquisition of skill, specifically, in the acquisition of automaticity. Nicholson and Fawcett

suggest that a reduced ability to concentrate on initial learning processes may be attributed to

working memory and attentional problems. It is plausible that difficulty in storing and

accessing information in working memory may affect the ability to automatise. Thus working

memory capacity could be related to the initial development of automaticity.

Working memory capacity appears to be a key factor in acquiring and retaining the

essential skill information needed to automatise skills. The storage and handling of

information from working memory are central to theories of skill acquisition (e.g., ACT

theory: Anderson, 1993) and automaticity (e.g., instance theory: Logan, 1988). For example,

the ACT theory defines skill acquisition as the firing of productions, whereby particular mental actions are triggered when a certain state occurs in working memory (Anderson, 1987). The instance theory describes learning as a race between an algorithm and an instance. Each time we perform a task we store a memory representation of the episode called an instance. The more instances that are stored, the probability increases of retrieving an instance before the algorithm is executed (Logan, 1988). Working memory is claimed to be responsible for the control of attention and processing, including retrieval of information from long-term memory (Baddeley, 2000). Thus, working memory is involved in the automatic retrieval of appropriate instances.

Alloway (2009) suggests that working memory capacity can be increased with training, which may then contribute to improved academic performance. Chein and Morrison (2010), Holmes, Gathercole, and Dunning (2009), and Thorell, Lindqvist, Bergman Nutley, Bohlin, and Klingberg (2009) found behaviour changes associated with working memory training extended beyond training situations, suggesting that working memory improvement assists in carrying out general cognitive skills. Furthermore, working memory training has been suggested to improve fluid intelligence, with working memory training improving coping mechanisms that deal with novel environment changes and abstract reasoning (Jaeggi, Buschkuehl, Jonides, & Perrig, 2008; Sternberg, 2008). The link between improvement in general cognitive ability and working memory training suggests that learning potential could be predicted on the basis of working memory measures. Thus, working memory ability may also predict the likelihood of learning retention and transferability of skills.

Whilst working memory ability has been linked to improved general cognitive ability it is important to note that there has been speculation around working memory training and its link to increased intelligence and academic achievement. Morrison and Chein (2011) suggest that improvements associated with working memory training may be linked to effort and

expectancy effects rather than as a direct result of the memory training itself. For example, motivation, commitment, and difficulty have not been previously controlled for amongst participants. Furthermore, there is almost no standardisation and convergence of the findings (Morrison & Chein, 2011). There appears to be great variability in the range of cognitive skills assessed and inconsistency in the stimuli and timing parameters in working memory research.

If working memory capacity determines the efficiency of cognitive performance, it is expected that a large working memory capacity should enable better cognitive performance. In the present experiment, two measures of working memory (the Swaps and the Triplets test) were implemented to explore whether people with larger working memory capacity attain automaticity faster than people with a smaller working memory capacity. Performance in the visual numerosity task according to training and transfer phases was compared with working memory performance. It was expected that those who reach automaticity faster in training may demonstrate no disruption in transfer trials due to a larger working memory capacity. This may indicate an ability to attend to changes in context better than those who have a smaller working memory capacity.

## Method

### Participants.

Twenty psychology students from Edith Cowan University voluntarily participated in the study. Participants were recruited via the ECU Cognition Research Group Participant Register. The inclusion criteria required participants to have 'corrected' or 'corrected-to-normal' vision and English as their primary language, and to not be colour blind. The participants' ages ranged from 17 to 65 years. Participants were reimbursed with a $20 shopping voucher for their time. During the recruitment phase, an information letter (see

Appendix B) was used to inform potential volunteer participants of the rationale and merits of the study. An informed consent form (see Appendix C) was used to obtain participant consent. The researcher verbally advised participants of the rationale and merits of the research, asked if they had any questions, and invited them to participate. The informed consent form reiterated that participation was voluntary and as such at any time they could withdraw from the study. The form also provided participants with another prompt to ask questions if there was anything they did not understand about the experiment.

**Design.**

The study utilised the two-part visual numerosity task used in experiment one. During training trials configurations of six, seven, eight, nine, 10, and 11 asterisks were presented 50 times each. During transfer trials the same six asterisk configurations were presented 25 times each. Each level of numerosity was presented by a colour: 6 red, 7 blue, 8 orange, 9 pink, 10 green, and 11 purple, with corresponding numbered and coloured keys on the response pad. The secondary task of each trial only occurred if the participant provided the correct answer for the primary task. In the secondary task participants were required to perform an addition problem in training trials, and a subtraction problem in transfer trials, with a response in the form of the answer being odd or even. Participants received feedback for incorrect answers in parts one and two. A new trial was initiated following the presentation of feedback.

The experiment also included measures of working memory, using the Triplets test and the Swaps test implemented via the ebilities website (ebilities, 2015). These tests were based on the test utilised in Stankov's (2000) experiments. For both the Triplets and Swaps tests, participants were required to report how confident they were that their test answer was correct as a percentage (e.g., 60%). The Triplets test provides a measure of fluid and crystalised intelligence and was used in this experiment as a measure of working memory. Participants are required to memorise a rule relating to the order of three numbers (a triplet)

and make decisions on whether or not the rule applies. For example, "Click on YES if the first number is the lowest number and the last number is the highest. Click on NO if this is not the first case". When shown a triplet, they must decide whether or not the rule they have memorised applies, using the mouse to click on the "Yes" or "No" button on the screen. The test becomes more difficult as the rules become more complex. There are 42 items in total in this task.

The Swaps test is a test of fluid intelligence that involves working memory. Participants are required to swap the order of the pictures shown (e.g., circle, triangle, rectangle, lines) with reference to the instructions on screen. Test items range between one to four swaps with item complexity increasing (i.e., more swaps are required). There were a total of 20 items on the test. Participants were shown a set of three pictures and were given instructions about swapping the order of the pictures (e.g., "swap 2 and 4"). An answer screen then appeared, which included the same three pictures in various orders. Participants were asked to select the option that presented the correct sequence of pictures after the swap had been made.

**Apparatus and stimuli.**

The experimental task had two parts, and there were two phases to the experiment (training and transfer) (total duration: 45–60mins). In the primary task of each trial, a configuration of asterisks, ranging in number from six to 11, was presented in the centre of a computer screen. In the training phase, the secondary task of each trial required participants to add a number (between one and six) to the number of asterisks just presented and respond as to whether the answer was odd or even. In the transfer phase, the secondary task of each trial involved subtracting a number (between one and six) from the initial number of asterisks (see Figures 18 and 19). Blocks consisted of the same number of trials in experiment one (six) with a matched secondary task. The training phase comprised of 50 presentations of

each configuration, and the transfer phase comprised of 25 presentations of each configuration.

Each asterisk was separated from other asterisks within a stimulus configuration by at least 1 cm vertically and horizontally. Dell personal computers were used to display the stimulus patterns, and a SuperLab (RB-840) response pad was utilised by students to report the number of asterisks presented in the primary task. There were six coloured keys on the response pad, marked six, seven, eight, nine, 10, and 11. In the secondary task participants were required to respond whether the addition or subtraction answer was 'odd' or 'even'. The response pad had two additional keys marked 'odd' and 'even'.

The Triplets and Swaps tests were conducted on the same Dell personal computers as the visual numerosity task. Participants entered their responses with the keyboard and mouse.

| Training trial | Primary task | | Secondary task | |
|---|---|---|---|---|
| * | *    *     *<br>*<br>*   *<br><br>How Many Stars? | | __ + 2 = __<br><br>Is the answer odd or even? | * |
| Fixation Point 250 ms | Answer 6 | Blank Screen | Answer Even | Fixation Point 250 ms |
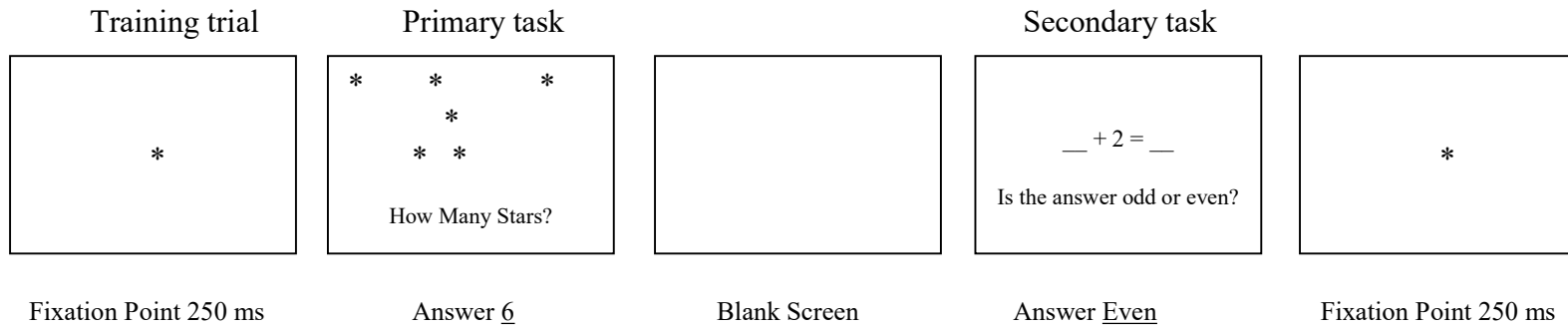
**Figure 18: Example configurations of the primary task and secondary task during training.**

| Transfer trial | Primary task | | Secondary task | |
|---|---|---|---|---|
| * | *   *    * *<br><br>*   * * *<br><br>How Many Stars? | | __ - 5 = __<br><br>Is the answer odd or even? | * |
| Fixation Point 250 ms | Answer 8 | Blank Screen | Answer Odd | Fixation Point 500 ms |
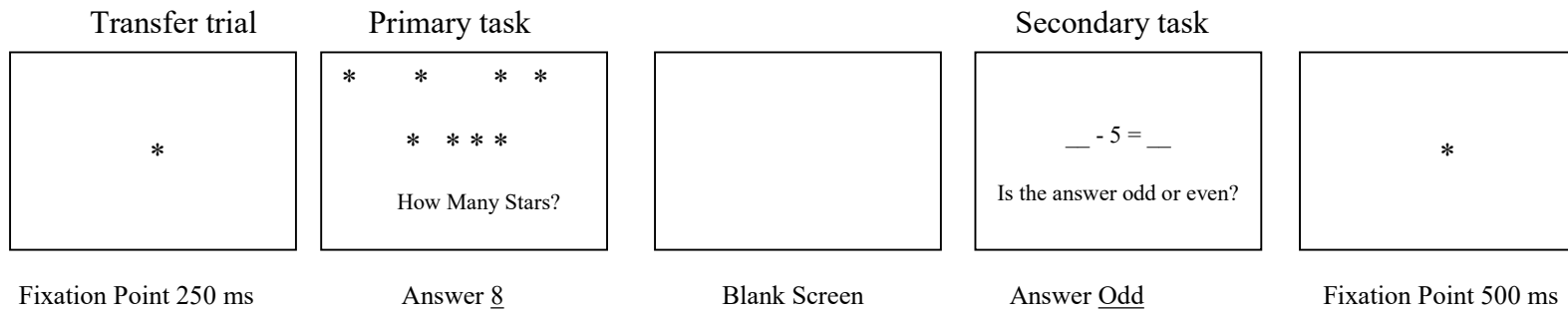
**Figure 19: Example configurations for the Transfer task**

## Procedure

Participants began the experiment by completing the Swaps and Triplets working memory tasks. Participants were given a personalised user id and password to login to the ebilities test site. Participants were asked to click on the Start Test button in the top right of the web page to access the site, then login using the provided details, and follow the prompts. After providing demographic information participants began the Swaps task. The Triplets task followed immediately after the Swaps test.

For the visual numerosity task a practice phase of 12 trials, utilising different example stimuli, was used to familiarise participants with the task. Once participants fully understood the procedure the training trials began. In the primary task of each trial a fixation point appeared in the centre of the screen for 250 ms, followed by a random configuration of asterisks (six, seven, eight, nine, 10, 11). The pattern remained on screen until a response was made on the response box by pressing one of the corresponding keys. A blank screen then followed for 250 ms. Participants were instructed to add a number to the configuration presented in the form of " __ + 2 = __ ". Participants were asked to respond "Is the answer 'odd or 'even'?" by pressing the corresponding keys. A subtraction problem was presented during transfer trials. Participants were instructed to respond as accurately and as quickly as possible. Participants were given an optional rest break after 25 blocks. Feedback was given for incorrect responses for the primary task and a new trial was presented. The incorrect trial was repeated again later in the same block.

## Results and Discussion

### Reaction time.

Average RT across all levels of numerosity for each block was calculated to investigate the pattern of learning and to enable visual inspection of the data for changes in

RT after block 51: the transfer phase. Only data from participants who attained a mean accuracy of 80% for the primary task of the visual numerosity task were analysed; however, no participants scored equal to or less than this cut-off point (Training: $M = 97.90\%$, $SD = 2.23$; Transfer: $M = 98.11\%$, $SD = 2.23$; Total: $M = 98.03\%$, $SD = 1.80$). Inclusion criteria also required participant RT performance to be less than 9000 ms for each trial. Trials that were identified as exceeding the maximum RT (9000 ms) were labelled as incorrect and were omitted from the analyses. Two participants chose to discontinue from the study; accordingly their data was excluded from the analyses.

Figure 20 shows the mean RT in each block plotted along with a power function with asymptotes constrained to zero that was fitted to the 50 blocks of training, and extrapolated a further 25 blocks into the transfer phase. Power functions provided a high degree of fit (high $r^2$ and low root mean squared deviation (rmsd) values) to the observed training RT (see Figure 20). The improvement in training RT with practice was well described by a power function.
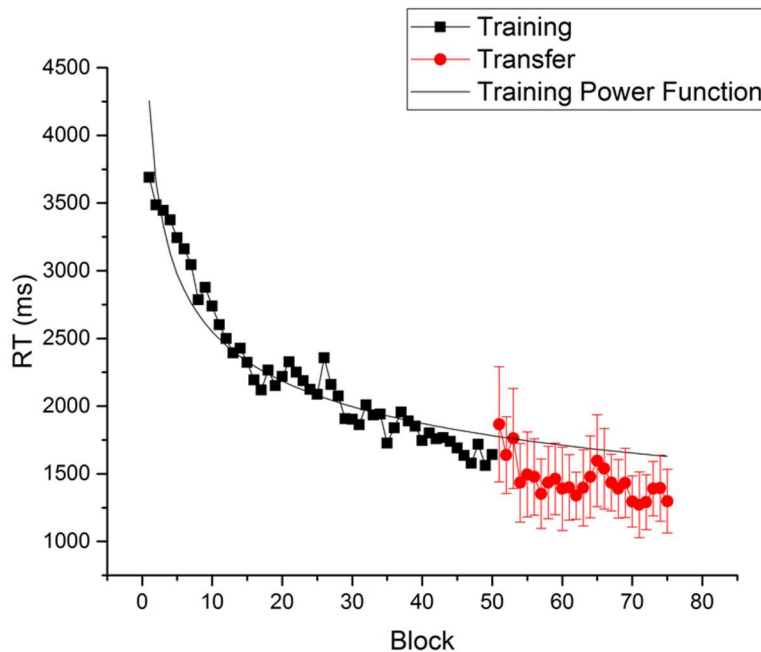
**Figure 20: Mean RT in the primary task of each trial.**

The smooth line is the best-fit power function (RT = 4256.71*Block$^{-0.22}$, r$^2$ = .96, rmsd =204.57). Error bars represent 95% confidence intervals. The power function was fitted to training data and extrapolated to the transfer phase.

### Disruption measure.

A one-way repeated measures ANOVA was used to compare primary task RT in the last block of training ($M$ = 1640.84 ms, $SD$ = 675.47) with the primary task RT in the first block of transfer ($M$ = 1866.20 ms, $SD$ = 885.62). The ANOVA results show that RT did not significantly differ between training and transfer blocks ($p$ = .06).

To assess the extent to which transfer performance could be predicted from training performance, the power function derived from the training phase data was extrapolated a further 25 blocks and compared with observed transfer RTs. Transfer performance is considered to be predicted well on the basis of training performance where extrapolated values pass within the 95% confidence intervals of the transfer RTs (Speelman & Kirsner, 2001) (see Figure 20). As a result, although RT appears to be slowing down early in transfer, this was not by a statistically significant amount.

The transfer results suggest that after an initial slowing of RT after the changes to the secondary task of the trial, subsequent RT appears to be unaffected. To examine how transfer performance is maintained after the initial readjustment in the first block of transfer a repeated measures ANOVA was conducted on transfer blocks 51, 52, 53 and 54. Mauchly's test indicated that the assumption of sphericity had been violated, $x^2$ (5) = 39.15, $p$ = .00, and so the degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\varepsilon$= .54). There was a main effect of transfer block, $F$(1.61, 57)= 5.10, $p$ < .05, with Bonferroni post hoc tests revealing that RT was significantly slower in block 52 of transfer ($M$ = 1637.86 ms, $SD$ = 131.85) compared to block 54 ($M$ = 1433.94 ms, $SD$ = 135.76), and block 53 ($M$ = 1761.22 ms, $SD$ = 172.05) was significantly slower than block 54. After the initial increase in RT in block 51, RT appears to decrease as the number of trials in transfer increase, particularly by block 54 where RT was significantly faster than in transfer blocks 52, 53, 54. After the slower RT in blocks 51 and 53, there was a general reduction in RT throughout transfer (see Figure 20).

**Individual performance (primary task).**

Figure 21 presents each participant's RT for the primary task of each trial, for all blocks in the experiment. It is apparent in this figure that not all participants demonstrated the pattern of RT improvement that was exhibited in the group average results. Participants three, seven, 12, 13, 14, 16, 17 and 19 display data patterns that could be considered similar to that observed in the overall RT data. In contrast, participant one demonstrated little change in RT with practice, which is a vast deviation from the collective RT data (see Figure 20). Participants two, four, five, six, nine, 10, 11, 18 and 20 all demonstrate sudden changes in RT at varying points in the data. Only eight out of 20 participants demonstrated either a linear relationship between performance and practice or similar performance trends to that observed in the group data. This suggests that individuals are not uniform in their approach to the task

and performance does not necessarily reflect classical learning curve performance for all participants.
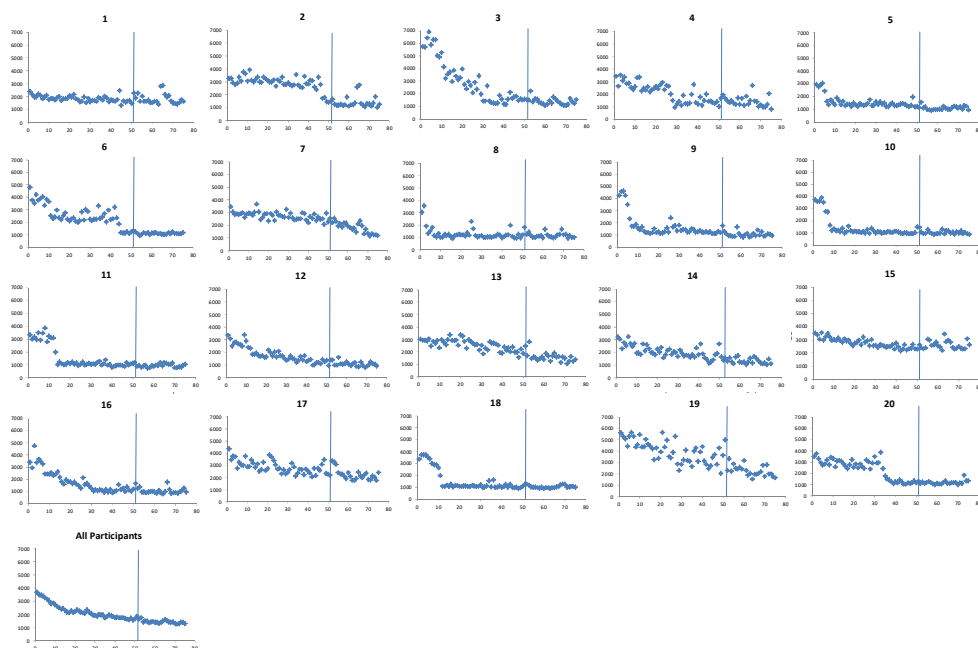


**Figure 21: Individual RT performance data for 20 participants and group RT performance data on the primary task of each trial. The figures represent RT (ms) as a function of practice (block).**

**Individual performance (secondary task).**

Figure 22 depicts individual performance in the secondary task to determine whether changes implemented in the transfer trials (block 51) impacted upon immediate performance. That is, were the changes challenging enough to cause a disruption in performance patterns? Figure 22 indicates that group performance on the secondary task of each trial had little disruption during transfer. Individual performance indicates that most participants (except participants one and 20) were not disrupted in overall transfer performance in blocks 51–75. Participants three, 15, 21 and 24 demonstrated RT performance similar to classic learning

curves. This suggests that there was little difference in difficulty between the secondary task

tasks in training and transfer.
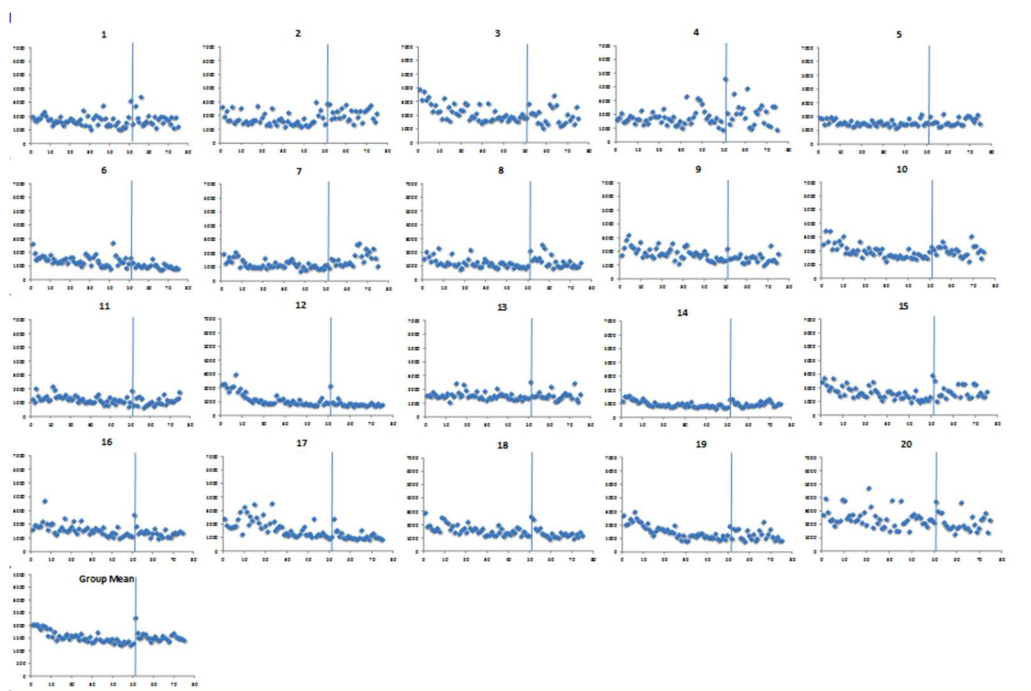


**Figure 22: Individual RT performance data for 20 participants and group RT performance data on the secondary task of each trial.**

## Automaticity

As expected, on the basis of the typical development of automaticity, early in training

RT on the primary task of each trial was directly related to the number of items presented on

screen. RT generally increased as the number of items on screen increased. The slope of this

increase in RT with numerosity was expected to be large during the early training phase but

should decrease as performance became more automated, with a value of zero expected

during the late training phase. Mean RT for each level of numerosity for each phase is

presented in Figure 23, which demonstrates that RT in the early phase of training increased as

the number of items on screen increased. In the mid phase the slope of the regression line was

shallower than in the early phase. RT was independent of numerosity in the late training

phase, with only a slight increase in RT with the increase in numerosity. This supports

previous research on the development of automaticity in visual numerosity with practice (Logan, 1988). RT was faster in the transfer blocks compared to training performance, which is consistent with scenario one (p. 46). Overall, participants did not quite meet criterion 1 for automaticity by the end of training; however they appear to have been closer to reaching automaticity during the transfer phase (see Table 3). This result suggests that automaticity has led to complete transfer, supporting the ACT-R and instance theories. Participants appear to have been unperturbed by the contextual change manipulated in this experiment.

Regression lines of the form RT = a + b*numerosity were fitted to the RT data for each participant as a function of numerosity for each of the training phases. The slope values for these lines are presented in Table 3. Participants were classified as having achieved automaticity using two criteria outlined in experiment one (Chapter 5). As indicated in Table 3, 15 (75%) participants were considered automatic by the late training phase, using criterion one, whereas 17 (85%) out of 20 participants were considered automatic using criterion two. Most participants appear to have approached automaticity by the late training phase.
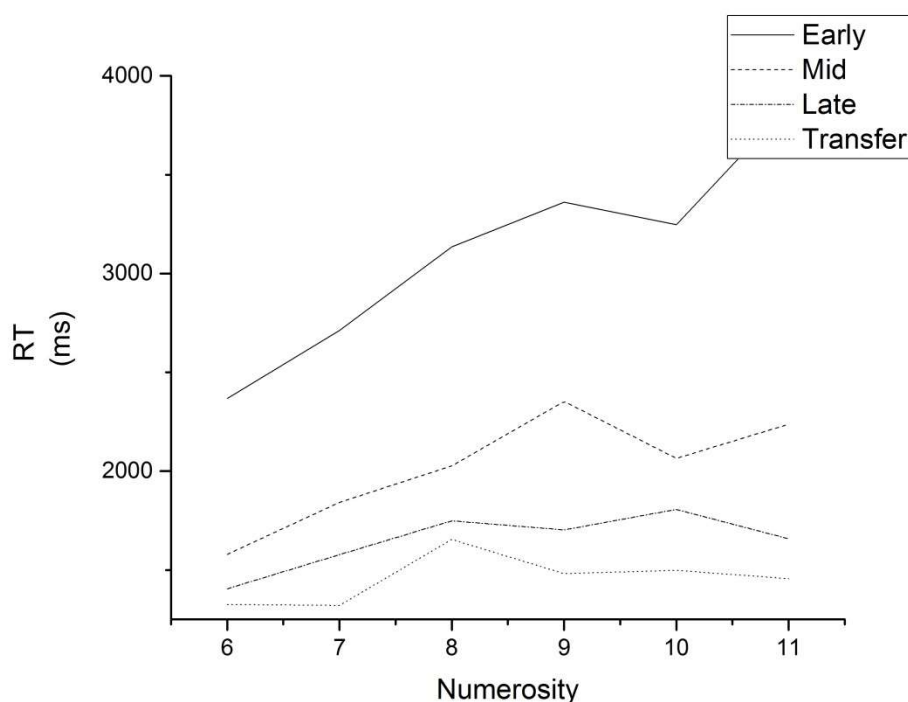
**Figure 23: Mean RT for the primary task of each trial as a function of numerosity for early, mid, and late training phases and transfer.**

Table 3 shows the $r^2$ values for the regression lines. It can be noted from this table that small $r^2$ values show no linear incline with increasing asterisks, indicating that participants have reached automaticity (i.e., their RT does not increase with number of asterisks). For those people with high $r^2$ values, the regression line does fit the data well, indicating a linear increase of RT with number of asterisks, which is evidence consistent with them not attaining automaticity yet.

Calculations of slopes indicate that performance was reaching asymptote by transfer trials, and mean RT between training and transfer indicates a minimal disruption in performance. The findings suggest that transfer performance continued in accordance with gains made in training performance. Context changes do not appear to have disrupted transfer performance. Two possible explanations can be considered in explaining why participants' transfer performance was unaffected by the change to the secondary task:

1)      Participants were automatic on this task and therefore changes to the secondary task in the transfer phase do not impact upon primary task performance. Thus, automaticity enables complete transfer. Logan (1985) states that a person who has attained automaticity can continue to improve their performance with practice. Thus these results suggest that participants may have continued to improve beyond automaticity and were undisrupted by context changes, as the theories, such as the ACT and the Instance theories, would predict.

2)      Or, participants were simply colour matching the stars to the coloured response pad. This would still support the development of an automatic response to colour matching, but with less challenging task requirements. Thus, changes to the secondary task are not enough to disrupt performance

on colour matching. With little impact on the slope of the RT-numerosity line in transfer with the context change, it is possible that the task was too easy, with colour coding resulting in little attention being paid to context changes.

Whilst trying to facilitate the development of automaticity through the use of colour coding in the visual numerosity task there appears to have been an effect on performance that may have reduced the challenge of the task significantly.

**Table 3: Participant slope of regression lines fitted to RT data as a function of numerosity.**

| Participant | Early slope | SD | Mid slope | SD | Late slope | SD | Transfer slope | SD | Criterion 1 Automaticity achieved (<100 ms) * | Criterion 2 Automaticity achieved (reduction of slope from early to late)** | Disrupted Y/N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 210.27(.84) | 428.88 | 219.14(.84) | 446.92 | 218.45(.77) | 466.11 | 149.12(.61) | 355.52 | 2 | 2 | Y |
| 2 | 165.97(.52) | 430.05 | 227.67(.76) | 487.38 | 335.68(.78) | 710.03 | -50.66(.15) | 243.45 | 2 | 2 | Y |
| 3 | 490.09(.82) | 1012.47 | -161.35(.17) | 727.92 | -144.64(.61) | 374.60 | -92.76(.37) | 284.49 | 1 | 1 | N |
| 4 | 302.91(.71) | 674.44 | 251.11(.31) | 836.78 | 66.41(.42) | 191.83 | 182.59(.71) | 404.61 | 1 | 1 | Y |
| 5 | 137.91(.52) | 357.50 | 14.57(.03) | 144.98 | 20.72(.06) | 156.01 | -12.63(.03) | 137.84 | 1 | 1 | N |
| 6 | 255.06(.51) | 670.96 | 236.95(.60) | 573.48 | 21.21(.02) | 302.30 | -15.73(.05) | 136.27 | 1 | 1 | Y |
| 7 | 253.00(.84) | 516.19 | 275.48(.86) | 554.21 | 380.94(.93) | 739.81 | 202.88(.36) | 631.89 | 2 | 2 | Y |
| 8 | 42.07(.02) | 516.17 | 172.01(.59) | 420.46 | -36.24(.14) | 182.19 | 14.02(.02) | 173.19 | 3 | 1 | Y |
| 9 | 33.84(.06) | 259.25 | 33.88(.21) | 139.64 | -38.8(.14) | 191.48 | -33.83(.08) | 222.55 | 3 | 1 | Y |
| 10 | 35.71(.09) | 216.31 | 9.65(.08) | 63.50 | 14.13(.08) | 95.38 | -18.56(.11) | 104.91 | 3 | 1 | N |
| 11 | 392.81(.79) | 825.01 | 22.65(.06) | 177.53 | 13.8(.04) | 136.97 | -17.25(.12) | 92.40 | 1 | 1 | Y |
| 12 | 257.29(.60) | 623.49 | 4.14(.00) | 871.17 | 16.26(.01) | 330.34 | 53.74(.25) | 200.59 | 1 | 1 | N |
| 13 | 186.12(.88) | 794.57 | 13.33(.37) | 615.26 | -35.49(.02) | 534.15 | -94.91(.03) | 468.84 | 1 | 1 | Y |

| Participant | Early slope | SD | Mid slope | SD | Late slope | SD | Transfer slope | SD | Criterion 1 Automaticity achieved (<100 ms) * | Criterion 2 Automaticity achieved (reduction of slope from early to late)** | Disrupted Y/N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 14 | 397.93(.88) | 789.78 | 199.15(.37) | 595.66 | -35.49(.01) | 614.16 | -41.55 (.03) | 486.01 | 1 | 1 | N |
| 15 | 304.4 (.65) | 609.80 | 144.49 (.11) | 400.83 | 97.27 (.12) | 220.40 | 154.35 (.00) | 411.53 | 1 | 1 | Y |
| 16 | 240.93 (.61) | 576.10 | 90.98 (.56) | 220.34 | -33.17 (.53) | 85.10 | 3.45 (.003) | 127.36 | 1 | 1 | Y |
| 17 | 581.75 (.86) | 1175.92 | 478.94 (.99) | 905.40 | 406.69 (.56) | 1016.68 | 360.93 (.42) | 1036.35 | 2 | 1 | N |
| 18 | 281.97 (.94) | 543.43 | -8.32 (.30) | 28.40 | 26.07 (.32) | 85.56 | -25.81 (.28) | 90.90 | 1 | 1 | Y |
| 19 | 484.96 (.74) | 1055.65 | 270.24 (.16) | 1281.57 | 111.20 (.03) | 1286.70 | -110.09 (.06) | 847.06 | 2 | 1 | Y |
| 20 | 276.82 (.74) | 600.60 | 324.73 (.72) | 716.37 | 14.46 (.10) | 86.40 | -22.55 (.15) | 107.03 | 1 | 1 | Y |

* 1 = automatic performance (i.e., slope <100 ms). 2 = non-automatic performance (i.e., slope >100 ms). 3 = automatic performance in early training phase.
** 1= automatic performance (i.e., slope decreasing from early to late training phases). 2 = non-automatic performance.

Three types of automaticity performance were identified (see Table 3) based on the slope of regression lines relating response latency to numerosity:

1) Automatic with practice as predicted based on the ACT and instance theories.

2) Little change in RT, with automaticity not attained by the late training phase.

3) Automatic early in training with the slope of regression relating to response latency reflecting small slopes close to zero early in task performance.

According to automaticity criterion one, the regression slopes of five of the 20 participants were never lower than 100 ms, suggesting that automaticity had not been reached. However, according to automaticity criterion two, only three participants were not considered automatic by late training. It is apparent according to individual results that not all participants are performing the task at an equivalent level. That is, even though participants have been given the best opportunity to achieve asymptote by late training via colour matching visual stimuli with responses, there are still those who continue to utilise counting methods for task execution.

Figure 21 suggests that not all participants are exhibiting the same learning pattern; some participants seem to be unpredictable in their performance. Two participants (three and 19) display learning curve patterns that would be considered typical RT performance; that is RT reduces as training trials increase. Interestingly, nine participants demonstrated a sharp reduction in RT at varying points of practice that were not reflective of any experimental changes. It seems as though these participants suddenly became attuned to the colour and numerosity congruence, which led to a rapid development of automaticity, followed by a reduction in learning gains as demonstrated by a plateau in performance.

What is clear by inspecting individual data is that individual results do not necessarily reveal uniform performance based on theoretical positions. Smith and Lerner

(1986) reported great deviations in the number of trials taken to reach asymptote by individuals, with the range reported to be between 10 and 100 trials. The current results support the idea of individual variability in learning curves.

Developing automaticity in this experiment was facilitated by reducing task demands whereby colours simply had to be matched to responses. Encouraging the development of automaticity in this way may have resulted in participants finding the experiment too easy, resulting in unfocused attention, or mind wandering (Kane et al., 2007) whilst performing the task.

## Disruption and Transfer

A measure of disruption for the primary task was calculated by subtracting, for each participant, the mean RT in the first block of transfer from the mean RT in the last block of training. A positive number indicates RT that is slower in transfer. As indicated in Table 4, 14 (70%) participants were disrupted in transfer performance. Six participants were not disrupted in transfer.

A large percentage (70%) of participants demonstrated a slowing of RT performance in transfer and a large percentage (75% according to criterion one and 85% according to criterion two) of participants were classified as automatic by the late training phase.

The primary interest of this study is whether automated performance on a primary task is affected by a change to a secondary task. The aforementioned results indicate that group performance can be considered automatic, and even at the individual level most participants reached asymptote by late training. It was hypothesised that given the current definition of automaticity and in light of recent findings, automaticity may lead to one of four possible outcomes (see Chapter 5). Automatic performance of a task could be

unaffected by context change (as demonstrated in no change in transfer performance with a change to the secondary task; scenario one), or only affect transfer momentarily (scenario three), or finally, appear to limit transfer performance suggesting automated skills are bound to the specific context in which they were acquired (e.g., Logan, 1988; Shiffrin & Schneider, 1977; scenarios two and four). A within subject ANOVA was conducted to compare primary task RT in the last block of training with primary task RT in the first block of transfer trials. No significant difference was found between these blocks.

Although the results do not indicate a significant increase in RT between the last block of training and the first block of transfer, there was an increase in RT performance times supporting scenario three predictions. This disruption may be interpreted as a momentary 'surprise' effect whereby participants were briefly interrupted in their execution of a learned mental set, and RT performance returned quickly after a brief readjustment and re-employment of an automatised strategy (Speelman & Parkinson, 2012). Although performance recovered soon after, as observed in blocks two and four, there was a period of time where participants may have second-guessed the strategies previously implemented and may have resorted back to older counting strategies.

The results of experiment two suggest that skill transfer has occurred in the primary task despite changes to the secondary task. When people became automatic on the primary task, changes to the secondary task did not affect performance of the primary task, especially if conditions that encourage the automatic performance (i.e., colour coding) still exist. That is, automaticity seemed to enable complete transfer.

**Table 4: Participant data from training and transfer blocks and working memory measures.**

| Participant | Mean RT (ms) training last block | Mean RT (ms) transfer first block | Disruption mean RT (ms) primary task | Training block 1RT (ms) - transfer block 1 primary task RT (ms) | Mean training RT (ms) first block secondary task | Mean training RT (ms) last block secondary task | Mean transfer RT (ms) first block secondary task | SWAPS accuracy (%) | TRIPLETS accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1469.17 | 2275 | 805.83 | 126 | 1950 | 1929.5 | 3101.5 | 95 | 90 |
| 2 | 1421.33 | 1470.67 | 49.34 | 1786 | 2610.67 | 1364.5 | 2889.33 | 75 | 90 |
| 3 | 1579.67 | 1555 | -24.67 | 4204.5 | 3878.17 | 1817 | 1782.2 | 55 | 83 |
| 4 | 1022 | 1685.5 | 663.5 | 1745.33 | 1594.2 | 864.33 | 4594.2 | 90 | 100 |
| 5 | 1212.67 | 1134.67 | -78 | 1791.16 | 1876.6 | 1537.33 | 1515.83 | 80 | 95 |
| 6 | 1241.33 | 1304.67 | 63.34 | 3498.73 | 2593.17 | 1170.83 | 1585.83 | 90 | 100 |
| 7 | 2282.17 | 2542.67 | 260.5 | 903.67 | 1947 | 1127.6 | 1157.5 | 95 | 95 |
| 8 | 1216.5 | 1816.5 | 600 | 1233 | 1878.83 | 1110.33 | 3491.4 | 90 | 100 |
| 9 | 1197 | 1755.5 | 558.5 | 2509 | 2138 | 1315 | 3372 | 65 | 100 |
| 10 | 1493.5 | 1446.33 | -47.17 | 2294 | 1531.67 | 997.33 | 2100.25 | 100 | 90 |
| 11 | 1097 | 1176.83 | 79.83 | 2148.83 | 1707.17 | 1312 | 2205.8 | 90 | 98 |
| 12 | 1371.5 | 966.8 | -404.7 | 2385.87 | 2477.33 | 1937.33 | 2263.4 | 45 | 88 |
| 13 | 1883.4 | 2453.8 | 570.4 | 572.03 | 2594.75 | 1711.4 | 1977.6 | 95 | 90 |
| 14 | 2677 | 1662.83 | -1014.17 | 1554.5 | 1248.5 | 1026.83 | 1838.6 | 70 | 76 |
| 15 | 2300.5 | 2644.17 | 343.67 | 862 | 2256.83 | 901.67 | 2129.8 | 50 | 93 |
| 16 | 1208.67 | 1689.83 | 481.17 | 1704.67 | 1733.83 | 1654.17 | 2491.83 | 100 | 100 |
| 17 | 2331.83 | 2286.2 | -45.63 | 2084 | 1517.33 | 1331.8 | 2511.8 | 90 | 86 |
| 18 | 977.67 | 1071.67 | 94 | 2311.93 | 1160 | 732 | 1311.83 | 75 | 100 |
| 19 | 3629.2 | 5004.2 | 1375 | 629.97 | 2430.67 | 1332.17 | 2911.5 | 55 | 86 |
| 20 | 1156.33 | 1289.67 | 133.33 | 2208.33 | 1617.5 | 1112.67 | 2677.17 | 85 | 98 |

**Transfer trial performance.**

Due to the nature of the experimental design the first trial of the first block of transfer reflects performance when the participant has not, as yet, been exposed to the context change. Therefore, mean RT in the first block of transfer (block 51) may not accurately represent the amount of disruption after the context change is implemented. In order to eliminate the possibility of a very fast RT score in the first trial of transfer, performance in the first block of transfer was examined on a trial-by-trial basis. As expected, performance on trial one of transfer was fast, with mean RT under 1400 ms (see Figure 24). In trial two, RT was substantially slower after the context change. Following the context change RT does not seem to return to the level of trial one transfer performance even as trial practice continues. RT remained slower than trial one in subsequent trials of this block. However, no significant differences were found in RT performance on a trial-by-trial basis.

Greater disruption in the secondary task was found to be related to slower RT in transfer. So it would appear that participants conceptualised the two-part task as one task so that a change from addition to subtraction in the secondary task generated a slower response in the primary task. These results appear to support the findings of Speelman and Kirsner's (2001) where a context change results in changes to learned skills and challenge theories of skill transfer, such as the ACT theory and the instance theory that infer automaticity should be a stable and durable process. What is apparent is that this disruption continued throughout block one transfer with a gradual shift in performance speed that may indicate a shift back to memory strategies. Similar to what Speelman and Parkinson (2012) found, there is evidence to reject the idea of a 'surprise' effect to explain the disruption in transfer due to the sustained effect of the disruption in block one of transfer.
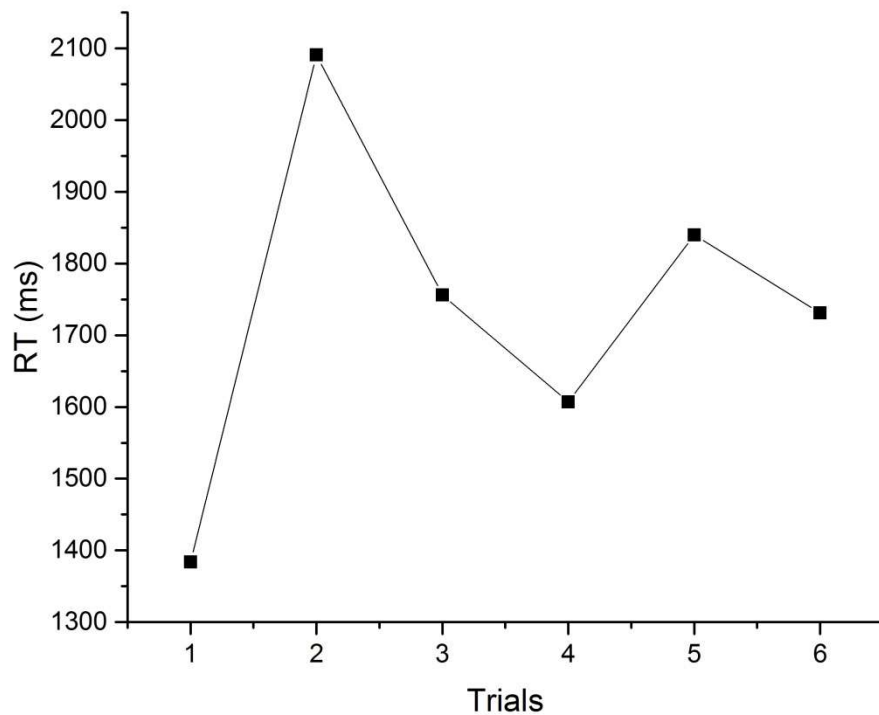
**Figure 24: Mean RT for the primary task on each trial in transfer block 51.**

*Accuracy.*

Throughout the experiment only correct answers were included in the analyses. Disruption has been considered as a slowing in RT performance; however, an increase in errors may also indicate that performance is affected by context changes. The number of correct answers was recorded for trial two immediately following the context change implemented in the trial one secondary task. Eighteen participants answered correctly, only one participant answered incorrectly. Another participant's data on trial two was recorded as incorrect due to not meeting the inclusion criteria (i.e., RT<900 ms). Accuracy of trial two performance did not indicate a disruption, and so cannot explain why most participants were slower on trial two than on trial one.

## Relationship Between Automaticity and Transfer

### Groups and disruption mean.

According to automaticity criterion one, the performance of participants 10, 11, and 12 were identified as automatic at the beginning of the task. Participant 12 demonstrated performance in transfer that was faster than their performance on the last block of training. Participants 10 and 11 were however disrupted in transfer performance. Five participants demonstrated no change in automaticity from the early to the late blocks (the regression line slopes did not demonstrate any notable increase or decrease), and of these participants four demonstrated a disruption in RT performance during transfer. Eleven participants (55%) demonstrated performances that suggest automaticity was established over time, with their regression line slopes decreasing below 100 ms by the late training phases. Four of these participants did not demonstrate a transfer disruption, with RT faster in transfer compared to the last block of training. Six of these participants were disrupted in transfer performance. At an individual level, then, there appears to be no consistent transfer performance outcome based on automaticity classification.

## Relationship Between Automaticity and Working Memory

To determine whether there was a significant relationship between measures of working memory and visual numerosity performance, a correlational analysis was conducted between the Swaps, Triplets, and RT performance on the last block of training and the first block of transfer, and slope of RT-numerosity regression lines (early, mid, late and training phases, and the transfer phase). A strong negative correlation was found between the Triplets performance ($M = 92$.90, $SD = 6.88$) and early slope values ($M = 266.59$, $SD = 150.18$), $r(17) = -.48$, $p < .05$. This suggests that participants who started the task with smaller slope values in the early training phase also performed well in the Triplets task, with many performing at or above 90% accuracy. It is plausible, then, that

those who have a high working memory capacity were also able to establish automaticity early in the visual numerosity task. This supports predictions that a high working memory capacity facilitates the development of automaticity. Significant correlations were found between the Triplets performance and mean RT of the last block of training ($M =$ 1638.42, $SD = 682.31$), $r(17) = -.66$, $p = .001$ (see Figure 25). Figure 25 indicates that the participants who achieved 100% in the Triplets task also had fast RTs in the late training phase. Therefore, working memory capacity may be important to facilitate faster performance on the visual numerosity task. All participants appeared to perform well in the Triplets memory task, with only one participant achieving lower than 80%. No other correlations were found to be significant.
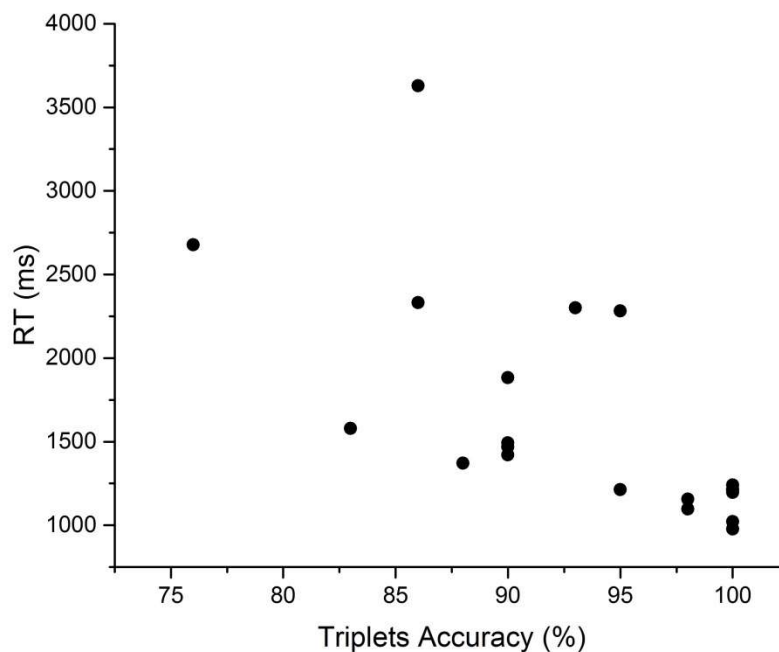


**Figure 25: Mean RT for the late training phase and Triplets accuracy performance.**

## Relationship Between Transfer and Working Memory

Correlational analyses revealed no significant correlations between the measure of disruption and working memory measures, so no clear connection can be drawn between these measures.

A measure of working memory was included to determine whether working memory capacity could be a predictor of automaticity and could account for individual differences in automaticity and transfer performance. Correlational analyses revealed that performance in the Triplets working memory test was linked to early training slopes of regression and RT performance in the last block of training. Participants who were considered automatic with slopes of regression close to zero also scored high on the Triplets test. Two participants obtained 100% accuracy and had slopes of less than 50 ms. Those who scored below 87% accuracy also demonstrated slopes of greater than 370 ms. These findings suggest that the way a participant approached the task—that is, whether memory strategies are implemented early on in the task as opposed to utilising only counting strategies—can be mediated by working memory ability. In other words, how well a participant does on the Triplets task may predict how quickly memory strategies are implemented and how automaticity develops.

Triplets task performance and early slopes close to zero may be explained through the research on problem-solving ability and working memory. Executive functioning is responsible for control of attention and processing (Baddeley, 2000), problem solving (Swanson & Beebe-Frankenberger, 2004), and the ability to inhibit irrelevant information into working memory (Chiappe et al., 2000). Executive functioning and working memory capacity are suggested to share a common executive attention component that has been found by McCabe, Roediger III, McDaniel, Balota, and Hambrick (2010) to be highly predictive of higher-level cognition. Furthermore, working memory is considered a

domain general component responsible for the control of attention and processing that is involved in a range of regulatory functions, including the retrieval of information from long-term memory (Baddeley, 2000). In the current experiment, the participants who demonstrated early small slopes and high Triplets scores may indicate a more competent domain general working memory component of processing that allows them to quickly work out the requirements of the visual numerosity task, leading to early establishment of automaticity. The current results suggest the ability to attend to task features to quickly work out a strategy can lead to reduced cognitive load and faster task execution. This would appear to support claims by Alloway and Alloway (2010) and McLean and Hitch (1999) that executive memory may control the ability to learn tasks to automaticity. However, in this experiment working memory does not appear to be statistically related to transfer disruption.

There were some noteworthy results in the individual data:

- Participants 10 and 11 both obtained 100% in the Triplets test and demonstrated minimal disruption (disruption RT under 600 ms) with slightly lower transfer slopes, compared to other participants.

- Participant three's performance in early training was high with a slope of 490.09 ms (however they did achieve a slope of -101.36 ms by mid training), they also scored 83% accuracy in the Triplets and demonstrated RT that was faster in transfer compared to the training last block.

## Conclusion

Thus far, group results indicate that automaticity may support skill transfer. Furthermore, working memory may be responsible for the rate of automaticity acquisition and successful transfer. Individual results indicate that individuals develop automaticity at

varying rates, and some do not even appear to approach automaticity after much practice, contrary to the average group results. The final experiment explored further the role of automaticity whilst attending to some concerns regarding experiment two—that is the addition of colour corresponding to numerosity configurations. The issue of automaticity and transfer performance cannot be reconciled in this experiment due to the possibility that the task was too easy, and so participants engaged in colour matching rather than implementation of counting and memory strategies and may have been subject to greater distractibility from the changes in context in the transfer trials. The intended aim for experiment two was to identify participants who varied in the degree to which they were automatic, that is to be able to identify those who may have relied on only counting strategies compared to those who implemented remembering strategies. By identifying differences in task strategy, it could have been determined whether automaticity related to transfer. Experiment two did not allow for this to be tested as most people were automatic early in the experiment. The design in experiment three was refined by removing the colour correspondence to refocus the participants to learn the pattern configurations through counting and remembering strategies, rather than just colour matching the configurations with the coloured keys. The experimental questions being addressed remained the same. No further changes to the experiment were implemented.

**Introduction to Experiment Three**

The findings of experiment one suggest that automatic skills can be disrupted by novel context changes. Group B2 demonstrated a significant slowing in RT performance with the transition from training to transfer, supporting the findings of Speelman and colleagues (i.e., Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2012). As participants were sporadic in the development of automaticity and individual characteristics could not account for the probability of transfer disruption, the findings were not consistent with any of the predictions outlined in Chapter 5. Instead, performance beyond the initial transfer disruption indicates that task approach or task conceptualisation may have differed between the two experimental groups. Differences in task difficulty rather than the impact of context changes may have been responsible for performance pattern disparities. Experimental design plays an important role in the manipulation of skill transfer and disruption, and thus congruence is required between the experimenter's intention and the participant's conceptualisation (Healy et al., 2005). Subsequently, experiment two was designed so that the experimental condition did not influence transferability.

This experiment was specifically designed to refine the experimental design and provide a more challenging task in order to maintain attention. The aim of the experiment was to determine how automatic skill performance on the primary task of each trial is affected by changes to the secondary task of the trial. The two research questions that were examined in experiments one and two were also central to experiment three. Specifically, this experiment investigated the extent to which automaticity affects transfer performance, and how much training is required to obtain the most successful transfer.

The results of experiment two indicated that RT performance did not significantly change with the transition from training to transfer. Whilst group results indicated

automaticity was established with the training trials, individual data revealed that some participants failed to even approach automaticity. The role of automaticity in skill transfer is difficult to examine when there are individual variances in the acquisition of automaticity and transfer disruption performance. Furthermore, the group results did not reveal any clear relationship between working memory capacity and the predictability of automaticity or skill transfer performance. However, according to individual results, greater working memory ability may lead to early establishment of automaticity, and appears to facilitate transfer performance. What was intended as a method of facilitating the attainment of automaticity—the addition of colour to the numerosity configurations and key responses—may have resulted in the task being too easy for the participants leading to a loss of attention to the secondary task and context changes. Accordingly, the third study in the present program of research aimed to rectify the influence of experimental design found in experiments one and two by removing the colour feature from the primary task of each trial. No further changes were made to the experimental design.

The interpretations and hypotheses generated in experiments one and two also applied to experiment three. If the transition from training to transfer trials were not disrupted, then context would appear to have no effect over automatic skills acquired in training, supporting the theoretical predictions of the ACT (Anderson, 1982, 1992) and instance theories (Logan, 1988, 1990) where automatised skills remain stable even under minor context changes. Conversely, if RT is disrupted with the transition to transfer, this would indicate that despite the primary task remaining unchanged, changes to the secondary task affect the ability to perform the primary task automatically, possibly through some conceptual adjustment whereby participants rethink the overall task requirements. Thus, some loss of automaticity may be apparent during the context

transition from training to transfer trials (Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2012). Performance after the initial few transfer trials is expected to indicate whether automaticity is beneficial or a hindrance to learning. If performance recovers and RT continues to decrease as the number of trials increase, automaticity would appear to be beneficial to overall learning despite the initial task re-conceptualisation. However, if RT does not recover after the initial disruption during transfer, this would suggest that automaticity is lost due to contextual changes.

Another purpose of this experiment was to determine whether individual differences in working memory capacity affect the ability to automatise performance of the primary task of each trial, and maintain primary task performance in the face of changes to transfer trials. The same measures of working memory capacity utilised in experiment two were also used in experiment three to explore the role of other variables in the link between automaticity and skill transfer, and thus, hypotheses remained the same for the current experiment. It was expected that a large working memory capacity should enable better cognitive performance. This may be evident by people with larger working memory capacity attain automaticity faster than people with a smaller working memory capacity. Furthermore, due to a larger working memory capacity, those who reach automaticity faster in training may demonstrate no disruption in transfer trials. This may be attributed to an ability to attend to contextual change better than those who have a smaller working memory capacity.

## Method

### Participants.

Twenty psychology students from Edith Cowan University voluntarily participated in the study. Participants were recruited via the ECU Cognition Research

Group Participant Register. The inclusion criteria required participants to have 'corrected' or 'corrected-to-normal' vision and English as their primary language. The participants' ages ranged from 17 to 65 years. Participants were reimbursed with a $20 shopping voucher for their time. During the recruitment phase, an information letter (see Appendix B) was used to inform potential volunteer participants of the rationale and merits of the study. An informed consent form (see Appendix C) was used to obtain participant consent. The informed consent form reiterated that participation was voluntary and as such at any time they could withdraw from the study. The form also provided participants with another prompt to ask questions if there was anything they did not understand about the experiment.

**Design.**

The study utilised the two-part visual numerosity task used in experiments one and two. Participants were asked to report the number of asterisks displayed on a computer screen for the primary task of each trial. During training trials configurations of six, seven, eight, nine, 10, and 11 asterisks were presented 50 times each. During transfer trials the same six asterisk configurations were presented 25 times each. Each level of numerosity was presented with corresponding numbered keys on the response pad. RTs and accuracy were recorded for participant responses in the primary task of each trial. The secondary task of each trial only occurred if the participant provided the correct answer for the primary task. In the secondary task participants were required to perform an addition problem in training trials, and a subtraction problem in transfer trials, with a response in the form of the answer being odd or even. Participants received feedback for incorrect answers in parts one and two, and a new trial was presented.

The experiment also included the same measures of working memory used in experiment two, the Triplets test and the Swaps test (see experiment two).

**Apparatus and stimuli.**

This experiment utilised the same numerosity configurations used in experiment two, however the colours were omitted from the stimuli and response keys. The secondary task included the same matched part two maths problem. All other details of the task were identical to experiment two (see experiment two for details).

**Procedure.**

Participants began the experiment by completing the Swaps and Triplets working memory tasks. The visual numerosity task was carried out in the same manner as in experiment two (see experiment two for details).

## Results and Discussion

**Reaction time.**

The average RT across all levels of numerosity for training and transfer blocks was calculated to investigate the pattern of learning and to enable visual inspection of the data for changes in RT after block 51, the transfer phase. Accuracy was screened to ensure that participants were not guessing in response to the task. Two participants obtained less than the accuracy cut-off point of a mean accuracy of 80% for the primary task of the visual numerosity task (Training: $M$=97.29%, $SD$=3.69; Transfer: $M = 97.08$, $SD$= 3.06; Total correct: $M = 97.22$, $SD$= 3.32) and were excluded from the analyses. The inclusion criteria were the same for experiments one and two, participants were required to maintain RT performance of less than 9000 ms for each trial. Trials that were identified in which RT exceeded the cut off of 9000 ms were labelled as incorrect and were omitted from the analyses.

Figure 26 shows the average RT performance in the primary task of each trial across all blocks. A power function was fitted to the training data with asymptotes

constrained to zero. A high degree of fit to the observed training RT was found for the power function (high r² and low root mean squared deviation (rmsd) values; see Figure 26), demonstrating that performance during training conformed to predictions based on the power law of learning (Newell & Rosenbloom, 1981).
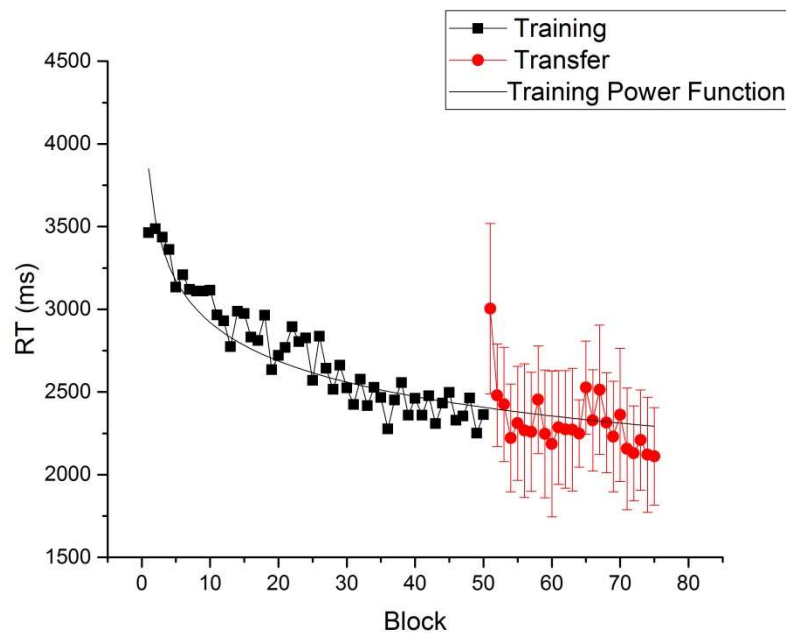


**Figure 26: Mean RT in the primary task of each trial.**

The smooth line is the power function that provided the best fit to the training phase data, and has been extrapolated in the transfer phase (RT = 3849.46*Block$^{-0.12}$, $r^2$ = .92, rmsd = 136.90). Error bars represent 95% confidence intervals.

**Disruption measure.**

To determine whether changes to the secondary task of each trial impacted upon the primary task transfer performance, a one way repeated measures ANOVA was used to compare the primary task RT in the last block of training ($M$ = 2363.32 ms, $SD$ = 745.42) with the primary task RT in the first block of transfer ($M$ = 3003.51 ms and $SD$ =1040.45). The ANOVA results indicate that RT did significantly differ between training and transfer blocks $F_{(1,17)}$ = 18.16, $p$ = .001.

The power function derived from the training phase data was extrapolated a further 25 blocks and compared with observed transfer RTs to assess the extent to which transfer performance could be predicted from training performance. Transfer RT in block 51 was significantly slower than training RT in block 50 with extrapolated values in block 51 passing below the 95% confidence interval of the transfer RTs (see Figure 26). After the initial significant increase in transfer RT, performance remains within the 95% confidence intervals of the predicted values. Thus, the results appear to support the findings of a conceptual adjustment (Speelman & Johnson, 2013; Speelman et al., 2011; Speelman & Kirsner, 2001) and appear to disprove the theoretical expectations of Anderson's ACT theory (1993) and Logan's instance theory (1988) of complete skill transfer.

The transfer results suggest that performance was initially disrupted, however subsequent transfer RT appeared to return to predicted values and thus would appear to have been unaffected by changes to the secondary task of each trial (see Figure 26). To examine how transfer performance was maintained after the initial readjustment in the first block of transfer, a repeated measures ANOVA was conducted on transfer blocks 51, 52, 53 and 54. Mauchly's test indicated that the assumption of sphericity had been violated, $x^2$ (5) = 17.11, $p$ = .004, and so the degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\varepsilon$= .67). There was a main effect of transfer block, $F$(1.81, 30.78) = 14.78, $p < .05$, with Bonferroni post hoc tests revealing that RT was significantly slower in block 51 ($M$ = 3003.51 ms, $SD$ = 245.24) compared to block 52 ($M$ = 2480.02 ms, $SD$ = 147.89), block 53 ($M$ = 2425.34 ms, $SD$ = 164.42) and block 54 ($M$ = 2221.22 ms, $SD$ = 155.14). After the slower RT in block 51, RT decreased as the number of trials in transfer increased, particularly by block 54 where RT was significantly faster than in transfer block 52. The results support evidence of a surprise effect (Speelman &

Parkinson, 2012) where, despite a significant disruption in transfer, performance continues in accordance with the power function that described improvement in training (Speelman & Kirsner, 2001). Furthermore, the results support Healy et al.'s (2005) findings that suggest primary and secondary tasks are conceptualised as a single functional task, and so, any change to a task's context will be interpreted as a change to the whole task.

**Individual performance (primary task).**

Figure 27 shows each participant's RT performance on the primary task of each trial for all blocks of the experiment. It is apparent from the figure that the performance of some participants is inconsistent with the trend observed in the group average results. For example, participants three, five, 14, and 16 appear to be varied in their RT performance, nonetheless all appear to be making gains in improvement. Participants four, six, seven, 10, and 18 display data patterns that could be considered similar to the group RT data. This suggests that individuals are not uniform in their performance, yet all seem to be improving with practice.

**Figure 27: Individual RT performance data for 18 participants and total RT performance data on the primary task of each trial. he figures represent RT (ms) as a function of practice (block).**

**Individual performance (secondary task).**

Figure 28 indicates individual and group performance patterns observed in the secondary task to determine whether the context change implemented in block 51 was challenging enough to disrupt performance. Overall group performance presents a typical improvement in RT as the number of blocks increase. However, individual performance shown in figure 28 suggests that not all participants conform to the same pattern in performance as demonstrated by the overall group results. Five participants (5, 6, 8, 14, 18,) demonstrate performance that is considered typical of learning curve patterns and similar to the overall group pattern of performance. Four (3, 15, 16, 17) out of 18 participants demonstrate varied performance with slow improvements in RT over time. This suggests that individual results do not necessarily conform to group result patterns. Deviations in performance demonstrated amongst these participants may indicate the effects of individual specific variables such as working memory differences. As expected, overall group performance on the secondary task of each trial indicates some disruption in block 51 (see Figure 28). Individual performance indicates that all participants (except for participants four, 10, and 14) were disrupted in transfer block 51.
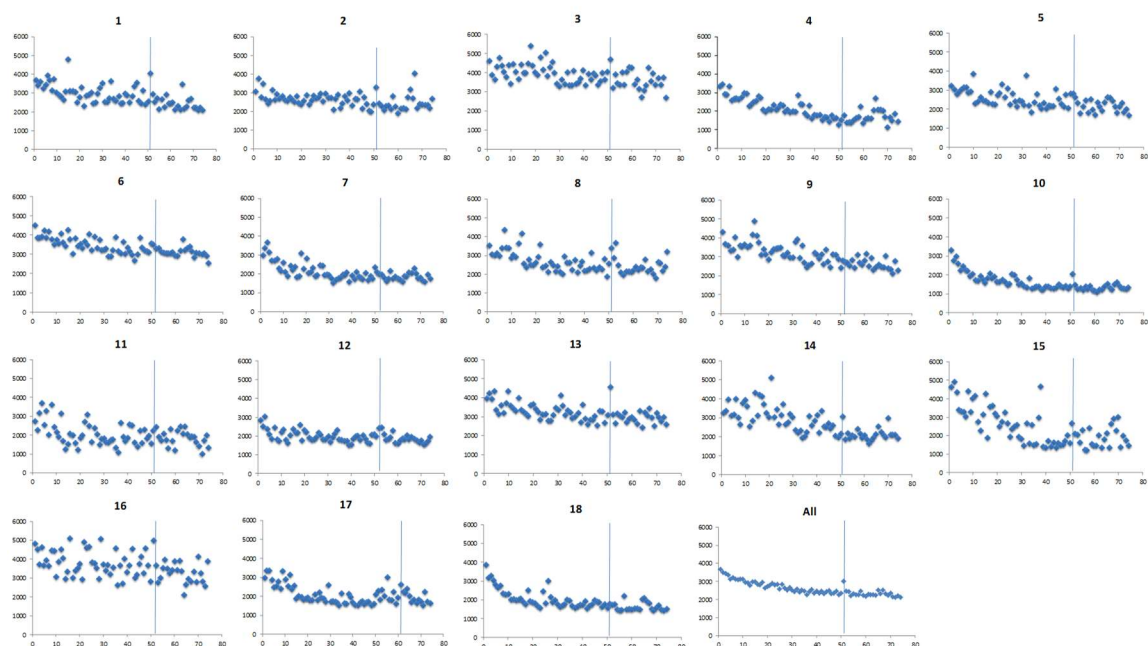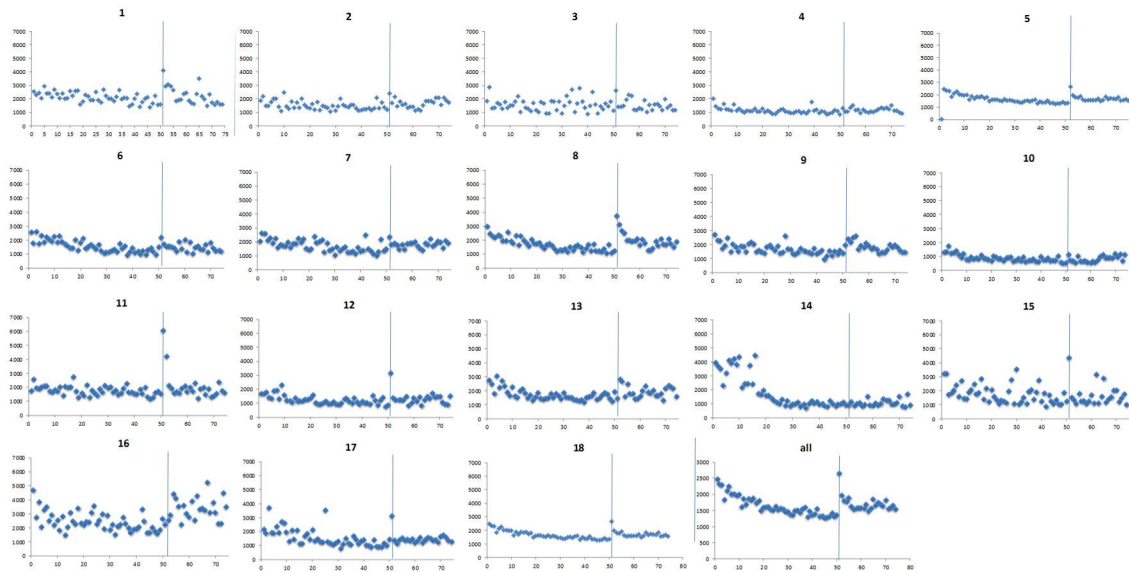
**Figure 28: Individual RT performance data for 20 participants and total RT performance data on the secondary task of each trial.**

## Automaticity

Mean RT for each level of numerosity for each phase is presented in Figure 29. As shown in this figure, typical development of automaticity is present in this sample, that is, performance early in training RT was directly related to the number of items presented on screen so that RT increases as the number of items increases until late in training where RT is independent of numerosity. In the mid phase the slope of the regression line was shallower than in the early phase, and then RT is independent of numerosity by the late training phase. This supports the classical demonstration of the development of automaticity in visual numerosity with practice (Logan, 1988). Performance in the transfer phase shows that the transfer line has a similar slope value to the late line, which suggest that practice during the transfer phase has not resulted in any further move towards automaticity. This contradicts findings in experiment two where slope values continue to decrease in transfer. Thus, the transfer results appear to provide support for scenarios one and three (see p. 46 of this thesis for scenario description), automaticity and transfer appear to be independent, automaticity is retained yet only

partial transfer is observed. That is, performance is initially disrupted, as indicated by the significant main effect of transfer block, however subsequent transfer RT appears to return to predicted values where performance speeds up after the initial RT increase at block 51. The results suggest that participants may be engaging in a reconceptualisation of the primary task, which supports Speelman and Kirsner's (2001) findings of an overhead in performance where any change to the context of the task leads to a reconceptualisation of the complete task. So, after an initial increase in RT, performance returns to pre-transfer performance levels.

Regression lines of the form RT = a + b*numerosity were fitted to the data for each person in each of the three training phases. The slope values for these lines are presented in Table 5. The same criteria utilised in experiment two were used to classify participant data as reflecting automaticity or not. As indicated in Table 5, group values suggest participants are approaching automaticity with a reduction in slope from early to late training phases, according to criterion two. Individual results suggest that the data of nine out of 18 (50%) participants were consistent with the pattern of change in group slope values. In contrast, only 44% of participants were identified as being automatic according to criterion one. Almost half of the participants appear to have approached automaticity by the late training phase.

The results indicate that overall participants improved their primary task RT as the number of trials increased. However, participants did not obtain a slope equal to zero or less than 100 ms by late training as was found in experiment two. The results suggest that counting methods may still have been used to perform the task, in contrast to memory retrieval methods that were expected to be in place after extensive practice. Therefore, whilst automaticity appears not to have been established by all participants in this experiment, overall the participants were approaching automaticity. Table 5 includes $r^2$

values for the regression lines describing the relationship between RT and numerosity. The participants whose results conform to the automaticity pattern or approach, all have very low (<.30) values for the mid and late phases.

Individual data was explored to determine whether participants differed in the extent to which automaticity was approached. According to automaticity criterion one, nine participants attained regression slopes greater than 100 ms, suggesting that automaticity had not been met in these participants. However, by utilising automaticity criterion two, only three participants could not be classified as approaching automaticity by late training. It was noted in experiment two only five participants were not considered automatic based on the same criterion grouping, thus, whilst the experimental design has succeeded in making the task more challenging, it is unclear why some participants were taking longer to automatise the task than others.
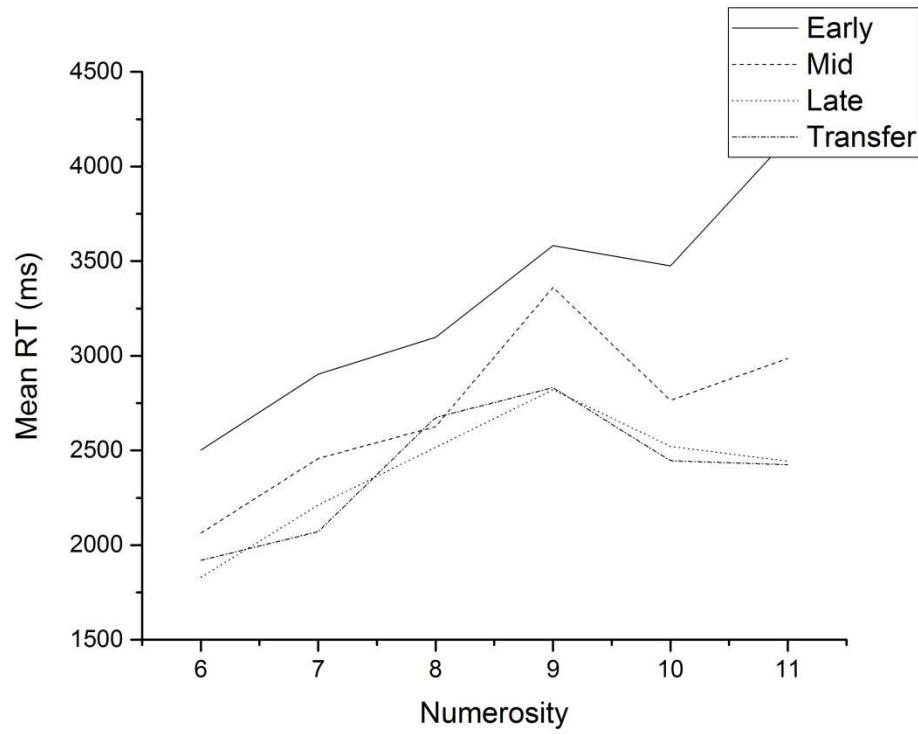
**Figure 29: Mean RT on the primary task for numerosity (6–11) in the early, mid, late and transfer phases.**

**Table 5: Participant slope of regression lines fitted to RT data as a function of numerosity.**

| Participant | Early slope | | Mid slope | SD | Late slope | SD | Transfer slope | SD | Criterion 1 Automaticity achieved (<100 ms) * | Criterion 2 Automaticity achieved (reduction of slope from early to late)** | Disrupted |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 157.83 (.42) | 456.28 | 264.35 (.71) | 585.67 | 329.44 (.66) | 759.33 | 164.46 | 550.38 | 2 | 2 | Y |
| 2 | 221.06 (.74) | 479.57 | 174.39 (.64) | 406.49 | 147.55 (.52) | 383.67 | 112.13 | 284.89 | 2 | 1 | Y |
| 3 | 194.95 (.21) | 794.14 | -21.02 (.01) | 416.48 | -45.1 (.02) | 568.59 | -10.89 | 889.39 | 1 | 1 | N |
| 4 | 106.44 (.23) | 413.79 | -16.02 (.00) | 645.95 | -77.38 (.15) | 377.59 | -221.77 | 607.60 | 1 | 1 | N |
| 5 | 425.72 (.94) | 819.79 | 335.25 (.75) | 717.78 | 377.09 (.80) | 788.69 | 223.73 | 554.89 | 2 | 1 | Y |
| 6 | 247.66 (.82) | 512.70 | 224.68 (.69) | 506.01 | 263.65 (.69) | 591.92 | 332.03 | 689.08 | 2 | 2 | Y |
| 7 | 336.01 (.68) | 762.67 | -95.78 (.07) | 679.51 | -71.43 (.07) | 490.14 | -84.03 | 531.42 | 1 | 1 | N |
| 8 | 381.07 (.81) | 790.91 | 305.30 (.81) | 633.08 | 218.92 (.92) | 427.94 | 318.33 | 632.32 | 2 | 1 | Y |
| 9 | 264.21 (.90) | 640.13 | 361.59 (.91) | 708.99 | 250.73 (.54) | 638.71 | 133.56 | 374.32 | 2 | 1 | Y |
| 10 | 318.85 (.84) | 651.69 | 41.37 (.09) | 311.65 | 6.13 (.00) | 256.80 | 52.87 | 280.07 | 1 | 1 | N |
| 11 | 193.07 (.38) | 586.15 | -15.49 (.00) | 780.71 | -126.67 (.07) | 871.98 | -118.5 | 764.73 | 1 | 1 | N |
| 12 | 277.37 (.85) | 563.74 | 90.37 (.27) | 327.66 | 59.12 (.08) | 387.53 | 105.51 | 336.12 | 1 | 1 | N |
| 13 | 367.46 (.50) | 975.69 | 254.99 (.32) | 845.06 | 248.84 (.55) | 626.55 | 133.78 | 587.93 | 2 | 1 | Y |
| 14 | 309.01 (.88) | 616.85 | 537.37 (.52) | 1387.09 | 232.21 (.34) | 750.18 | 101.53 | 617.44 | 2 | 1 | Y |

| Participant | Early slope | | Mid slope | SD | Late slope | SD | Transfer slope | SD | Criterion 1 Automaticity achieved (<100 ms) * | Criterion 2 Automaticity achieved (reduction of slope from early to late)** | Disrupted |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 15 | 625.63 (.58) | 1534.20 | 86.52 (.13) | 448.98 | -54.47 (.25) | 202.04 | 121.62 | 517.10 | 1 | 1 | N |
| 16 | 447.66 (.70) | 997.38 | 551.07 (.84) | 1125.53 | 450.31 (.78) | 950.71 | 544.66 | 1220.41 | 2 | 2 | Y |
| 17 | 290.94 (.83) | 597.51 | 108.88 (.24) | 1971.15 | -11.66 (.00) | 386.69 | 45.54 | 511.02 | 1 | 1 | N |
| 18 | 216.73 (.52) | 558.54 | 38.69 (.01) | 621.26 | -65.27 (.12) | 357.61 | 2.4 | 301.77 | 1 | 1 | N |

* 1 = automatic performance (i.e., slope <100 ms). 2 = non-automatic performance (i.e., slope >100 ms). 3 = automatic performance in early training phase.

** 1= automatic performance (i.e., slope decreasing from early to late training phases). 2 = non-automatic performance.

**Relationship between automaticity and transfer.**

A measure of disruption for the primary task of each trial was calculated by subtracting, for each participant, the mean RT in the first block of transfer from the mean RT in the last block of training. A positive number indicates RT that is slower in transfer. As indicated in Table 4, 14 (78%) participants were disrupted in transfer performance according to this measure. Four participants were not disrupted in transfer.

The relationship between automaticity and transfer was further examined to determine whether an individuals' training performance could predict the amount of disruption demonstrated in transfer. A correlational analysis was conducted between the slope of late training and a measure of disruption. This was not significant. However, Table 5 suggests that the larger the slope (further away from zero) the greater the disruption (with RT increasing in transfer).

*Transfer trial performance.*

Due to the nature of the experimental design the first trial of the first block of transfer reflects performance when the participant has not, as yet, been exposed to the context change. Therefore, mean RT in the first block of transfer (block 51) may not accurately represent the amount of disruption after the context change is implemented. In order to investigate the possibility of a very fast slow RT in the first trial of transfer affecting the overall mean value for block 51, primary task performance in the first block of transfer was evaluated on a trial-by-trial basis. A repeated measures ANOVA indicated that mean RT significantly differed between trials $F (2.57, 48.74) = 7.26, p = .001$. Post-hoc tests revealed that RT in trial two was significantly slower than trials one, four, and six (see Figure 30). Trial one was significantly faster than trials three and five, and trial three was significantly slower than trials four, five and six. Trial five was significantly slower than trial six. RT performance

from trial 2 got faster as the number of trials increased, demonstrating a recovery from the
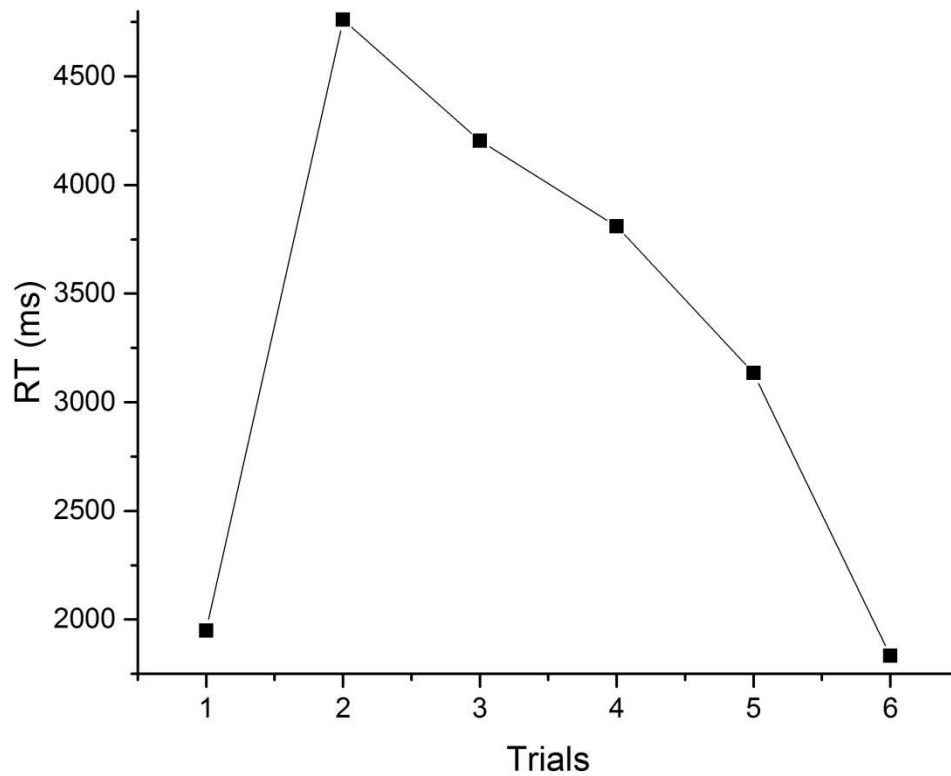
initial transfer disruption.



**Figure 30: Mean RT for the primary task of each trial in transfer block 51.**

*Accuracy.*

As in experiment two, errors in the trial two primary task were identified to determine

whether the observed transfer disruption could be identified as an error in numerosity

detection. Four participants (22%) answered incorrectly in trial two of transfer.

**Table 6: Participant data from training and transfer blocks and working memory measures.**

| Participant | Mean RT (ms) training last block | Mean RT (ms) transfer first block | Disruption mean RT (ms) primary task | Mean transfer RT (ms) first block secondary task | SWAPS accuracy (%) | TRIPLETS accuracy (%) |
|---|---|---|---|---|---|---|
| 1 | 2579.33 | 4071.6 | -1492.27 | 4071.6 | 55 | 93 |
| 2 | 2385.5 | 3311.5 | -926 | 3311.5 | 70 | 98 |
| 3 | 4052 | 4693.17 | -641.17 | 4693.17 | 55 | 86 |
| 4 | 1291 | 1547.67 | -256.67 | 1547.67 | 100 | 98 |
| 5 | 2837.33 | 2830.5 | 6.83 | 2830.5 | 75 | 88 |
| 6 | 3558.83 | 3514.67 | 44.17 | 3514.67 | 45 | 90 |
| 7 | 2362.5 | 2125.5 | 237 | 2125.5 | 90 | 98 |
| 8 | 2576.5 | 3399.5 | -823 | 3399.5 | 95 | 95 |
| 9 | 2431 | 2820.17 | -389.17 | 2820.17 | 80 | 90 |
| 10 | 1399.83 | 2066.83 | -667 | 2066.83 | 100 | 100 |
| 11 | 1572.5 | 2246.8 | -674.3 | 2246.8 | 80 | 90 |
| 12 | 2102 | 1996.5 | 105.5 | 1996.5 | 40 | 86 |
| 13 | 3105 | 4563.17 | -1458.17 | 4563.17 | 35 | 79 |
| 14 | 2168.5 | 3071.67 | -903.17 | 3071.67 | 55 | 100 |
| 15 | 1600.83 | 2677 | -1076.17 | 2677 | 75 | 88 |
| 16 | 2833.5 | 5008.17 | -2174.67 | 5008.17 | 40 | 90 |
| 17 | 2103.5 | 2315.83 | -212.33 | 2315.83 | 90 | 98 |
| 18 | 1580.17 | 1803 | -222.83 | 1803 | 90 | 90 |

**Relationship between automaticity and working memory**

Participants one, 14, 15, and 17 demonstrated a large disruption between training and transfer, of over 1000 ms. The aforementioned participants also scored low on the Swaps working memory test, with scores of under 55% accuracy (see Table 6). The results indicate that working memory may have a role to play in the participants' ability to adapt and utilise appropriate strategies. This suggests that performance in the numerosity task in the last block of training could be related to the amount of disruption demonstrated in the first block of transfer. A correlational analysis indicated no significant relationship, however visual inspection of the data suggests a larger slope in the late phase of training was associated with a greater disruption of RT transfer performance. Thus, participants who have slopes further away from zero may have difficulty in adjusting to context changes compared to those who have automatised the task.

**Relationship between transfer and working memory**

To determine whether there is a significant relationship between measures of working memory and performance on the visual numerosity task, a correlational analysis was conducted between the measures of working memory - the Swaps and the Triplets test – and the slope of performance during early, mid, late and transfer phases. The following variables were significantly correlated; Swaps test ($M$ = 70.55, $SD$ = 21.95) and late slope ($M$ = 118.45, $SD$ = 181.33) was significant and negative, $r$ = -.54, $p$ <.05; Swaps and transfer slope ($M$ = 108.72, $SD$ = 176.97), $r$ = -.51, $p$ <.05; Swaps and mean training last block ($M$ = 2363.32, $SD$ = 745.42), $r$ = -.62, $p$ < .05; and mean transfer first block ($M$ = 3003.51, $SD$ =1040.45) and Swaps test, $r$ = -.69, $p$ = .001. The results suggest that the participants' approach to the task (i.e., the ability to implement memory strategies as opposed to counting strategies) is related to their performance on the working memory task, and thus their ability to automatise the visual numerosity task is associated with their working memory test scores. Participants who

were faster in the training and transfer tasks were more likely to also have higher accuracy in the working memory tasks.

## Conclusions

The results of experiment three indicate that group performance may not be considered automatic. At an individual level only 50% of participants can be considered automatic with slopes less than 100 ms (Lassaline & Logan, 1993). Furthermore, the slope of linear regression by late training is higher (118.45 ms) than the late training slope value reported in experiment two (53.82 ms), suggesting that overall participants may not be considered as automatic as they were in experiment two. Further to this, there was a significant increase in primary task RT in the transfer phase of experiment three, suggesting that a lack of automaticity may be related to the transfer disruption. The findings would appear to support the inferences drawn from the ACT and instance theories. It was suggested by theoretical interpretations of these theories that automaticity may lead to one of three possibilities; automaticity would be unaffected by context change; or, only a momentary impact upon RT would be demonstrated, or, performance would be affected resulting in automaticity being bound to the context of which they were learned under.

# Chapter 6: Main Discussion

The principle focus of this thesis was to clarify whether automaticity facilitates or inhibits transfer. If positive transfer was observed (i.e., RT remains unchanged for the primary task with the transition from the training phase to the transfer phase), this would suggest that automatic skills are unaffected by contextual changes (prediction scenario one). Conversely, if transfer was disrupted (i.e., RT in the primary task increased over transfer trials), this would suggest that contextual changes result in a conceptual readjustment of the task causing participants to rethink task requirements (Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2012).

The results presented in this thesis indicate partial skill transfer occurred in all three experiments, supporting prediction scenario three (p. 86). However, inspection of the attainment of automaticity and subsequent transfer performance suggests varied support for scenarios three and four (reported in Chapter 4) across the three experiments. In all experiments, primary task RT improved with practice and was described well by a power function, suggesting that performance was in accordance with the power law of learning (Newell & Rosenbloom, 1981). Furthermore, all conditions demonstrated performance commensurate with the typical development of automaticity (Chi & Klahr, 1975; Lassaline & Logan, 1993; Logan, 1988), whereby the late training phase RT was independent of numerosity. Thus, the results replicate the general findings reported by Lassaline and Logan (1993); with practice, the visual numerosity task resulted in a change of performance with RT. Early in practice numerosity was a function of RT (i.e., RT increased as the number of items on screen increased due to a counting strategy), whereas later in practice RT became independent of numerosity (i.e., RT was no longer related to the number of elements on the screen, as configurations of elements were remembered as opposed to counted). These results can therefore be explained by the typical account that performance has moved from a

controlled form of processing early in practice (i.e., counting asterisks in a serial manner) to automatic processing (i.e., subjects recognised each stimulus and remembered the number of asterisks in the picture).

Power functions derived from training data were extrapolated (a further 50 blocks in experiment one, and 25 blocks in experiments two and three) and compared to observed transfer RT. All experiments demonstrated transfer performance that was not significantly different to predicted times; the extrapolated values passed within the 95% confidence intervals centred on the observed RTs. Despite some individual disruptions in transfer performance, overall, transfer performance conformed to predicted RT values based on extrapolating training performance in each of the three experiments. However, mixed conclusions can be drawn regarding the establishment of automaticity in each experiment. Inspection of individual data confirmed diverse individual performance patterns, which in some cases deviated a great deal from the typical performance trends that describe group performance. The following section considers the group findings and individual data trends for each of the three experiments.

## Summary of the Findings

### Experiment one.

In experiment one, overall performance trends of both experimental conditions indicated that partial skill transfer occurred. Specifically, primary task RT in condition B1 did not significantly increase in the transition from training to transfer trials, suggesting support for prediction scenario three. However, in condition B2 primary task RT was significantly disrupted between training and transfer trials, which was consistent with scenario four. Yet, the mean RT performance in block 101 was not as slow as the first block of training, and so scenario three may better explain the performance trend.

In experimental condition B1 automaticity appeared to facilitate transfer performance in subsequent trials beyond the initial disruption for this condition. However, performance in condition B2 suggested automaticity may be lost due to context changes with transfer RT remaining slower than training RT after the initial context disruption. This is reflected in Figures 13 (condition B1) and 14 (condition B2) where differences in disruption (or readjustment) impact are evident. One explanation for such differences in performance recovery was offered relating to perceived task difficulty or complexity of the counterbalancing measure.

Speelman and Kirsner (2001) suggest that an increase in complexity leads to greater transfer disruption than a decrease in complexity. If this is a general rule, then it suggests that the change from a subtraction operation to an addition operation in the secondary task of each trial in condition B2 may represent an increase in complexity. As the number of items on screen increased in the addition task, this difficulty affected performance in the primary task where participants may have resorted to inefficient methods, such as counting. This is indicated in Figure 17 where the slope of the regression line that relates RT and numerosity increased in transfer compared to what it was at the end of training. Speelman and Kirsner reported that performance in their experiments continued to improve in accordance with training performance after an initial disruption, however performance in condition B2 revealed that improvements during transfer were disrupted. In the more complex task condition participants might have second-guessed the requirements of both primary and secondary tasks, and may have continued to do so throughout the transfer trials. That is, an increase in complexity in transfer may have inadvertently affected primary task performance. Participants might have resorted back to more conservative task strategies, such as counting the asterisks in the primary task, rather than remembering the configurations from previous trials even though the configurations in primary task were familiar.

The extent of the disruption impact may also be related to the performance patterns exhibited in training. The control group showed a shift in performance from controlled towards automatic processing, yet slope values remained above 170 ms, suggesting that automatic skills had not been established to the criterion suggested by Lassaline and Logan (1993). Sixty-seven per cent of participants exhibited performance consistent with the group data findings. Logan and Klapp (1991) reported that automaticity could be achieved in as little as 36 repetitions of 12 stimuli, yet the participants in all conditions of this experiment did not demonstrate the typical reduction in slope values to less than 100 ms.

The findings in experiment one were not consistent with any of the predictions outlined in the introduction. It was concluded that the stimuli utilised in the secondary task might have assisted in implementing counting strategies for the duration of the experiment, and the conceptualisation of the primary and secondary tasks as one continuous task. This suggests that differences in participant RT associated with experimental condition were influenced by the experimental design. Thus, experiment two was specifically designed to refine the experimental design. Changes were made to the second part of the task in visual appearance and strategy requirements. The primary task remained the same, however the secondary task was simplified to increase the chance of automaticity developing and to distinguish the primary and secondary tasks more clearly.

**Experiment two.**

In experiment two, the group results suggested that automaticity was retained despite context changes in the transfer phase, with no significant differences found in primary task RT between the last block of training trials and the first block of transfer trials, indicating complete skill transfer occurred (prediction scenario one). Group results suggested that automaticity was retained despite novel context changes. However individual results revealed

that some participants (15%) failed to approach automatic performance. Despite the simplification of the task, some participants seemingly refused to give up slower counting strategies. This raises the question of whether individual characteristics, such as working memory ability and task approach, may predict whether automaticity is acquired and maintained. Regression slopes reached asymptote by transfer trials (criterion one) with slope values less than 100 ms by late training, and mean RT indicated a minimal disruption between training and transfer; thus, transfer performance appeared to continue in accordance with gains made in training performance.

The group results in experiment two did not clearly indicate whether or not automaticity plays a role in skill acquisition and transfer, nor did they indicate whether working memory might be related to the rate of automaticity acquisition or successful transfer. Individual results provided an even more uncertain connection. What was revealed was that individuals develop automaticity at varying rates, and some do not even appear to approach automaticity after a great deal of practice.

Although the design of the numerosity task was altered to facilitate automaticity through the use of colour in the visual numerosity task, it appeared that this may have reduced the challenge of the task significantly. In experiment two, the task appears to have been too easy for participants, resulting in an inaccurate depiction of automaticity and transfer performance.

One interpretation of the results of experiment two is that participants became automatic on the primary task, and changes in the secondary task did not significantly impact upon the performance of the primary task. As a result, participants continued to improve on the primary task, despite having already attained automaticity. However, it is possible that participants might simply have colour matched the asterisks to the coloured response pad. Although this still would constitute the development of an automatic response of colour

matching, it may be considered less challenging than pairing a numerosity configuration to a numerically labelled response pad. Thus, changes to the context of the secondary task in experiment two were not enough to disrupt performance on a simplified colour-matching task.

### Experiment three.

Experiment three was designed to increase the complexity of the primary task by removing the colour condition in order to ensure the participants learned (memorised) the pattern configurations; all other design elements remained the same.

A significant difference in RT was found between training and transfer blocks. In order to determine whether the disruption in RT performance was a momentary disruption or surprise effect, trial-by-trial data were explored to determine whether performance remained slower than the RT performance observed in training. After the initial slowing of RT, RT appeared to recover and learning gains appeared to increase as the number of trials increased. Figure 26 indicates that RT performance in block 54 decreased beyond predicted performance indicated by the power function fit, suggesting that performance was faster than expected based on training performance gains.

The results obtained in experiment three suggest partial transfer occurred and demonstrate support for prediction scenario three. Group results indicated that participants improved in RT performance as the number of trials increased, and can therefore be considered to have approached automaticity (criterion two) by late training. Yet, the participants in this experiment appeared to have failed to attain automaticity as defined by criterion 1 of achieving a slope value of less than 100ms by late training phases. Interestingly, context changes appeared to have disrupted non-automatic performance. Thus, it would appear a lack of automaticity might be responsible for a disruption in performance.

Inspection of individual data indicated that nine participants (50%) demonstrated performance that was consistent with group performance slope values. With 50% of participants failing to approach automaticity by late training, the results suggest that counting methods might still have been used to perform the task in contrast to memory retrieval methods that were expected to be utilised after extensive practice. It was noted in experiment two only five participants were not considered automatic based on the same criterion grouping, thus, the task used in experiment three may be considered more complex than the task used in experiment two. Whilst the experimental design has succeeded in making the task more challenging, some participants were still taking longer to automatise the task.

Overall, group results from experiment three indicated that participants were approaching automaticity. Yet, the group results may not reflect a transition from controlled to automatic processing in this experiment. No conclusions can be drawn from this data regarding the relationship between automaticity and disruption according to group classification.

**Working memory.**

A measure of working memory was included in experiments two and three to determine whether working memory capacity could be a predictor of automaticity performance and could account for individual differences in automaticity and transfer performance. Both the Triplets and Swaps working memory task performance were related to training performance. Correlational analyses reveal that in experiment two average performances in the Triplets working memory test was linked to early training slopes of regression and RT performance in the last block of training. Participants who were considered automatic with slopes of regression close to zero by late training also scored high on the Triplets test. Two participants who obtained 100% accuracy in the Triplets task also had slopes of less than 50 ms by late training. Those who scored below 87% accuracy also

demonstrated slopes of greater than 370 ms by late training. These findings suggest that working memory ability may influence the way a participant approaches the task or whether they can apply memory strategies early in training. Upon individual inspection of the data in experiment two, participants who obtained 100% accuracy in the Triplets test also demonstrated varying degrees of transfer disruption and were also automatic in the numerosity task (criterion one) by the late training phases. It is plausible then that greater working memory ability may lead to the establishment of automaticity, and appears to hinder transfer performance. Thus, a large working memory capacity may facilitate task strategy execution and the development of automaticity, but reduce the ability to transfer automatic skills.

In experiment three it was found that performance on the Swaps memory test correlated with late training slopes. This suggests that high working memory capacity is related to RT performance on the visual numerosity task. Large working memory capacity could mean better implementation of remembering strategies and better overall cognitive performance of other tasks, thus enabling quicker adaptation to the task and more flexible attention and task response. This supports the findings of experiment two. Individual data analysis revealed participants who demonstrated a large disruption between training and transfer of over 1000 ms, also scored low on the Swaps working memory test with scores of under 55% accuracy, indicating that working memory may have a role to play in the participants' ability to adapt and utilise appropriate strategies.

According to group results in experiments two and three working memory did not appear to be statistically related to transfer disruption. Experiment three however, revealed no consistent patterns of working memory performance, automaticity attainment or transfer disruption. Despite the lack of a statistically significant relationship between automaticity, skill transfer, and working memory in the two experiments, it is clear that specific participant

characteristics might be responsible for performance variation. As it is well documented that working memory is involved in the processing and storage of information in order to carry out cognitive tasks, it would be expected that working memory is involved in the development of automaticity of task components. The working memory task employed here might not have tapped into the specific requirements of the visual numerosity task. That is, the Triplets and SWAPS working memory tests only provide one measure of fluid and crystallised intelligence. A series of working memory test batteries may better indicate whether individual differences in automaticity and disruption in the visual numerosity task is related to working memory function.

### The role of automaticity in transfer.

The current results suggest that learning a skill to automaticity may facilitate transfer, supporting the theoretical interpretations of the skill acquisition theories. For example, when an individual encounters an identical representation of a task previously encountered, the existing task representation can be reused despite changes to the surrounding context or secondary tasks. That is, the general production rule for the primary task is still initiated and implemented due to the identical task elements of the primary task conditions (Anderson, 1982). Alternatively, the instance theory of automaticity (Logan, 1988, 1990) may also explain the current results. Logan (1988, 1990) suggests that skills are specific to the context in which they are acquired and may be difficult to transfer to a new context. In the current study, as the primary task remained the same, the specific events regarding the primary task that were encountered were also encountered in the transfer task; thus transfer would be expected to occur as compatible instances could be recalled from memory.

A momentary disruption was evident in the transition from training to transfer trials. According to Speelman and colleagues (e.g., Speelman et al., 2011; Speelman & Kirsner, 2001; Speelman & Parkinson, 2012) this may be attributed to a conceptualisation

readjustment. That is, participants may attempt to reconceptualise task requirements after a change to the secondary task is introduced. When a transfer disruption is observed, this may indicate that a set of skills, which were used in the training task, are no longer effective in a new transfer environment (Speelman & Parkinson, 2012). That is, the skills, which were developed to perform the primary task of each trial in training, cannot be used in transfer; therefore a reassessment of the task is required. As training performance recovered in subsequent trials (experiments two and three, and condition B2), this suggests that participants were able to employ previously learned strategies once participants realised that task requirements remained the same.

As indicated in experiments one, two, and three participants were sporadic in their development of automaticity and automaticity criteria grouping did not indicate whether automaticity development and transfer disruption could be predicted based on RT performance. Whilst the group results suggest a shift to automaticity where primary task RT was independent of numerosity, this was not consistent amongst all participants. Some participants did not attain automaticity—a finding that has not been reported widely in the literature.

In experiments two and three, participants who had high working memory scores could be considered to have a more competent domain general component of working memory processing than those with lower scores. As a result, the former individuals may have the ability to quickly work out the task requirements and appropriate task strategy leading to a reduced cognitive load, and faster and earlier automaticity establishment. This is consistent with the claims of Alloway and Alloway (2010) and McLean and Hitch (1999) who suggest executive memory may control the ability to learn tasks to automaticity. However, the current results provide no further insight into the individual characteristics of

those who do not reach automaticity and those who are affected by the disruption differently. What has been highlighted is the influence that factors, such as working memory, may play in the utilisation of learning and transfer strategies. Further research is required regarding individual differences in factors such as working memory capacity to determine why some participants deviate away from group data trends and why they may be affected differently by context changes.

### Limitations.

Whilst the results of the current study have some important implications for the consideration of the role of automaticity in transfer, these need to be considered within the context of a few limitations. Firstly, the experiments reported in this thesis have focused on performance associated with automaticity (i.e., RT) as a means of exploring the relationship between automaticity and transfer. However, specific mediators of automaticity (i.e., deliberate attention to repeated stimuli or attention to changes on the secondary task) have been overlooked in the current study and in previous research. Attention to the repeated nature of the task may assist in mediating the acquisition of automaticity more quickly. Furthermore, changes to the secondary task may not impact upon primary task performance as participants may be expecting the primary task to repeat as it has in previous trials. Expertise research (i.e., Ericsson, Krampe, & Tesch-Römer, 1993) supports this notion that deliberate skilled practice, where attention and focus is directed, may be a requirement for the development of automaticity.

For example, simply instructing the participants that the trials on the primary task will be repeated may help to develop automaticity through the use of memory strategies. That is, by instructing participants to use memory strategies automaticity may be more likely to develop. It has been found that explicit automaticity (i.e., knowledge of rules leading to

automaticity) leads to a greater disruption of performance than implicit automaticity (Masters, 1992). However, previous research has not considered the role of implicit versus explicit acquisition of automaticity and the effect of changes to a secondary task. Thus, future research could explore whether automatic skills are likely to be disrupted depending on whether they received implicit (no knowledge of rules) versus explicit (knowledge of rules) instruction.

Further to this, how someone approached a task may vary amongst participants and affect the development of automaticity and the impact of transfer disruption. Accuracy implies a careful response where counting may prove to be more useful than making a best guess judgement. Participants who might take a more conservative approach may be more reluctant to give up counting strategies and thus more likely to take longer to reach automatic skill performance. Future research could explore psychological traits, such as conservatism and confidence, in predicting the attainment of automaticity and subsequent disruption effects when faced with novel context changes.

## Summary

The findings reported in this thesis suggest that partial transfer can occur in the presence of automatic skills. However, transfer was also reported even without automaticity being established in training (experiment three). Current theoretical interpretations cannot account for the inconsistent results found in the experiments reported here. However, there are a number of possible explanations that may account for why some participants developed automaticity and were disrupted in transfer. For example, the two-step design of the experiment may have facilitated a serial task approach. In experiments two and three the presentation of the primary task was matched with a secondary task, thus both the primary and secondary tasks were still interrelated. Consequently, the presentation of the primary and

secondary tasks together may have contributed to the development of a mental set (Speelman & Parkinson, 2012) or single functional task representation (Healy et al., 2005). Thus, the context change to the secondary task resulted in a change in strategy from memory to counting for the primary task even though the primary task remained the same. Due to the two-part nature of the task, a change to the secondary task seems to cause participants to rethink what is coming next. That is, a combination of serial task association by a single functional task representation, and mental set development may explain why some participants were disrupted in the primary task, with changes to the secondary task context.

Chase and Simon (1973) state that automaticity is a requirement of learning; however, based on the results of the experiments reported here, there is more to consider about learning than just automaticity, such as prior learning experiences and motivation. As most skills are learned to be recalled reliably and automatically, motivation may need to be steered away from just learning quickly, to learning efficiently by consciously applying strategies that will be useful in achieving automaticity. Performance may be better, faster and more accurate if the skill is learned to automaticity, but the time taken to get there may be longer if using the wrong strategy, or automaticity may not be achieved altogether. This raises the question of whether we must wait for skills to become automatic before moving on in task complexity or attempting higher order tasks. The current results indicate that automaticity is not always established as quickly as the theories would suggest in previous studies (i.e., Lassaline & Logan 1993). Furthermore, there are individual differences in the attainment of automaticity, and for some, transfer of automatic skill occurs, yet for others any change to the surrounding context impacts upon automatic skill transfer.

The instance theory (Logan, 1988) holds that automaticity is a product of automatic recall of episodic representations accumulated over past experiences. Thus, by simply increasing experience with a task, automaticity will develop. However, in light of the results

of the experiments in this study it is evident that individuals come with their own set of experiences and abilities, and that simple exposure will not facilitate automaticity 'automatically'. Perhaps deliberate skill strategies that support automaticity are needed. This leads to the possible link between the measures of working memory and transfer performance.

By relying on group results one could easily conclude in this experiment that automaticity may result in transfer of training and that other factors, such as working memory, may be related to the transfer of cognitive skills but are not as important as the need for automaticity. However as Speelman and McGann (2013) point out, mean-dominant analysis can lead to theoretical error. In the current study, by ignoring individual differences in task performance, important considerations, such as individual learning patterns, could lead to the continuation of ineffective education strategies, such as learning by rote. It was not evident in this study that automaticity appeared to inhibit skill transfer, nor was automaticity required for successful transfer; individuals appeared to be able to adapt to context changes with or without the establishment of automaticity. Consequently, in the educational context learning to automaticity may not be the most suitable learning strategy for all students.

An issue raised in Chapter 1 was whether automaticity is achievable according to the current definition. The current results suggest that automaticity does not occur automatically for some individuals. This, in turn, suggests in an education setting repeated exposure to component tasks does not mean that higher order learning will automatically occur. Instead, a new definition of automaticity is needed; one that includes consideration of individual performance factors such as working memory capacity and deliberate strategy choice.

## Conclusion

Overall, the results appear to be congruent with Lassaline and Logan's (1993) findings. According to group data, automaticity appeared to facilitate transfer, and performance continued in accordance with the power law of learning theories. Automaticity was transferred to the new task and a change in context did not disrupt automaticity; however, automaticity does not appear to be reliably present amongst all participants. This highlights the difficulty of generalising group findings to individuals. According to group data, automaticity does not appear to hinder skill transfer and thus may be considered an integral part of the acquisition of skill and transfer of learning. The current findings provide an insight into whether performance of a previously learned (automated) task is maintained when context changes are made. However, due to inconsistent results in the individual data caution must be taken when generalising the findings. Empirical and theoretical literature, as well as educational and remedial or therapeutic practices, would benefit from further research to determine whether automaticity is found consistently to assist in skill transfer.

What began as a partial replication of the transition to automatic processing by Lassaline and Logan (1993) and exploration of the extent to which automatic performance mediates transfer performance, was extended to an investigation of whether automaticity is attained automatically as indicated by individual data, and whether individual variables can predict the acquisition of automaticity in the transfer of skill. Individual data indicates that not all participants behave the way the group data suggests. The current results question whether automaticity should be the desired outcome in education settings as many people failed to achieve automaticity according to common definitions. Automaticity may not be the desired state to facilitate skill transfer. Many participants did not demonstrate performance similar to average group performance; therefore, at an individual level automaticity may not be the best the best learning state. Studies, such as that of Kolozsvari et al. (2011), have

demonstrated automaticity (referred to as overlearning) to be of little benefit to skill transfer and retention. Yet, Dehabadi, Fernando, and Berlingieri (2014) highlight that whilst further research is required before automaticity (as measured by proficient secondary task performance) may be considered a proficiency measure in simulator training, it may still be in the best interest of training to strive for automaticity in such situations as simulator laparoscopy until more is known about the nature of automaticity in skill transfer. Further research is required at an individual level that includes psychological and performance factors to determine why some participants deviate from group data trends, and why they may be affected differently by context changes.

The discrepancies between individual results suggest that interpretation of group statistics needs to be taken with caution. Formulating therapeutic and remedial programs based only on group results may have a profound impact upon those individuals who do not necessarily conform to group performance patterns. Exploring individual predictors of performance may be used to identify whether skill transfer is likely to occur in a group of individuals, and would therefore assist in identifying the likelihood of the success of an educational program based on individual performance characteristics. Future research beyond skill acquisition and transfer research would also benefit from exploration of individual data trends.

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# Appendices

## Appendix A: Response Pad Example
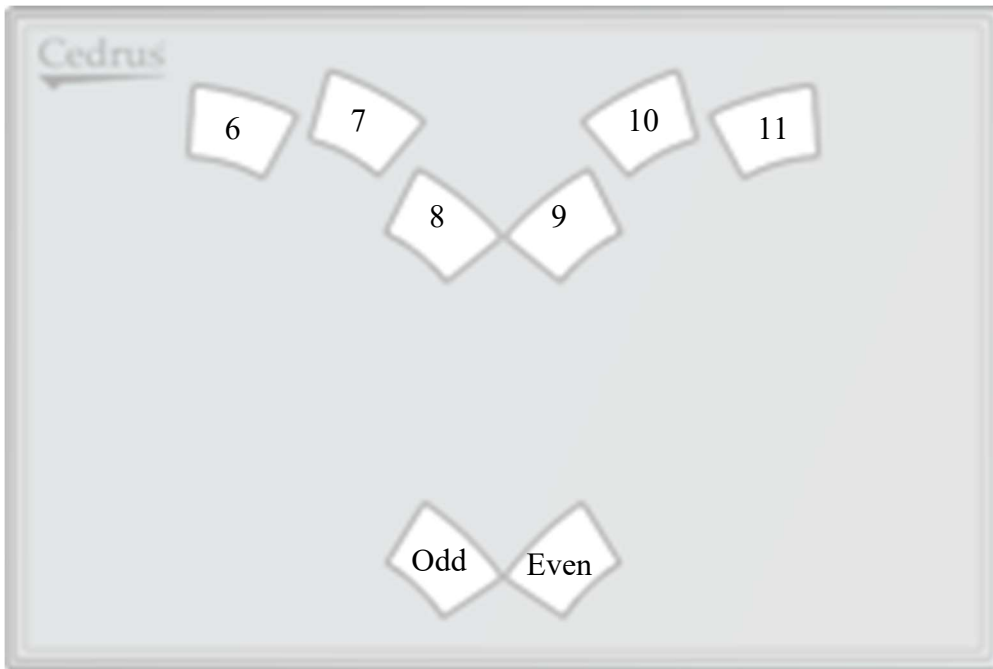
## Appendix B: Information Letter

**Thank you for your interest in this study. My name is Katrina Muller-Townsend. I am a PhD researcher from Edith Cowan University.**

The aim of my research is to investigate the nature of automated recall during a visual numerosity and working memory task. It is hoped that this area of research will reveal which type of learning is optimum in a classroom situation; context specific automatic recall, or context rich flexible knowledge, which may assist educators in providing the best learning situation in early education.

Your involvement will require participation in two computer tasks of approximately 1.5 hours in total and you will be rewarded with a $10 Westfield voucher for your time. You will also receive a ticket to go into the draw for a $50 gift voucher. Your participation is totally voluntary and anonymous; if you feel you would like to withdraw from the study you are free to do so at any time without penalty.

If there are any queries of questions in relation to the present study, please do not hesitate to contact myself:

0403 703 004
Email: klmuller@student.ecu.edu.au

If you wish to speak to my primary supervisor, Professor Craig Speelman on:
(08)6304 5724
Email:c.speelman@ecu.edu.au

Alternatively if you have any concerns or complaints about the research project and wish to talk to an independent person, you may contact the Research Ethics Officer:
(08)6304 2170

Regards,

Katrina Muller-Townsend

## Appendix C: Informed Consent Form

I _____ agree to participate in the PhD Research study about the role of
Automaticity in Skill Acquisition and Transfer, conducted by Katrina Muller-Townsend of
Edith Cowan University. I give written consent that:

- I have read the information letter and understand the purpose of the study.
- I have asked question s or queries that I have about any part of the research, and have been
  answered sufficiently.
- I understand information that is disclosed will be confidential, and any identifying
  information will not be revealed without written permission.
- I will be voluntarily partaking in this study.
- I understand that information given will be only used in a research thesis given to my official
  examiners at Edith Cowan University. However, I accept that this report may be published
  under the provision that I am anonymous.
- I understand that I may be recontacted by the researcher if necessary, and I understand my
  right to request a preliminary copy if desired.
- I understand my right to withdraw from the project at any time, and any information already
  disclosed will be destroyed and removed from the research. I also understand there will be no
  penalty from withdrawing from the research project.
- I understand I can obtain a signed copy of this consent from if requested.


_____          _____
Participants Signature          Date


_____
Contact number