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Automaticity as a predictor of skill transfer

Jana Melis
Edith Cowan University

USE OF THESIS

Automaticity as a Predictor of Skill Transfer

Jana Melis

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Automaticity as a Predictor of Skill Transfer

Abstract

Research into the effect of automaticity on skill transfer has resulted in conflicting conclusions about how automatic processes act on the transferability of skill. The research in this study was designed to investigate the existence and nature of the relationship between automaticity in skill acquisition and the ability to transfer that skill to a different task. Using a quantitative research design, a simple counting exercise was used to train participants in a skill, with the amount of training manipulated between groups. Accuracy rates and reaction times were recorded and analysed to determine the variance within and between the groups between initial training, final training, and transfer blocks to gauge the degree of skill transfer as a function of the amount of practice (degree of automaticity). Theories of ACT (Anderson, 1981, 1982, 1983) and Instance theory (Logan, 1988) of skill acquisition are detailed and applied to outcomes to explain characteristics of the underlying mechanisms of acquiring skill and the ways they account for improvements toward automatic performance. Furthermore, varied research and views on the affects of automaticity on skill transfer are outlined and applied to elucidate the outcomes in the analyses of results. Outcomes indicated that performance improved with increased training. This was demonstrated both over trials within the groups, and by comparisons between the groups in their final training blocks. Linear regression analysis of the data was conducted to observe changes in performance as a function of the number of stars that appeared in the stimuli. These too showed greater levels of automaticity were approached with extended training. The participants who received the most training showed less variation in performance despite the numerosity of stars than did those who received less training by the end of the training phase. Finally, correlation analysis between slope (*m*) values and reaction time differences between final training and transfer blocks indicated that those participants who received the greatest amount of training also experienced the greatest amount of disruption to performance when presented with the initial transfer task. The findings of the study are discussed in relation to skill acquisition and previous observations of the effects of automatic performance on transfer. It is concluded that the results indicate it is possible that varied degrees of automaticity could be used to gauge skill transfer.

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Date 21/1/2011 *..*

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Automaticity as a Predictor of Skill Transference

Individuals constantly pursue and carry out activities that all require some degree of skill (Speelman & Kirsner, 2005). Skills are necessary to perform a vast array of tasks, from complex social-cognitive skills such as generating and correcting causal attributions (Deutsch, Gawronski, & Strack, 2006), to the coordination of motor skills required to play a musical instrument (Berryhill, 2006), or the cognitive ability to reason and correctly calculate the answer to a mathematical problem (Touron & Hertzog, 2009). With repeated execution of these activities it is apparent that they can be carried out with increased proficiency.

Skill Acquisition

The transition from basic, crude performance to the mastery of a task is known as skill acquisition and is believed to involve a number of integrated component processes (Watson, 1993). Several theories have been postulated to explain the mechanisms underlying the progression of skill acquisition in attempts to explicate the links between improvements in ability observed with practice, and the associated cognitive processes. Two of the leading theories in this domain are that of the Adaptive Control of Thought theory (ACT) (Anderson, 1981, 1983, 1996) and Instance theory (Logan, 1988). In the ACT theory, Anderson suggests that improvements in efficiency of underlying algorithmic methods employed to resolve tasks explain increases in the facility of improved task execution (Lacey, 2007). Alternatively, Logan's Instance theory (1988) proposes that the accumulation of instances in which particular tasks are successfully carried out offer a collection of memories available for retrieval on how to perform these skills.

The study described in this thesis was designed to explore the relationship between automatic skilled performance and skill transfer. Automatic performance, termed automaticity, is the development of cognitive processes that underlie skill acquisition from slow, controlled performance to fast, effortless task execution. This occurs with practice and improvements in performance, as measured by decreases in reaction time and enhanced accuracy, continue to increase until an optimum level is reached. The second element of the investigation concerns skill transfer, which is the ability to apply learned techniques from one task to another, different task. Previous research suggests that greater transfer will occur between tasks that require similar cognitive processes for their successful execution as opposed to those that do not.

Research concerning the processes of skill acquisition is divided by the two main theories of ACT (Anderson, 1982) and the Instance theory (Logan, 1988). These theories differ in their perspectives on the cognitive mechanisms that control the development of skilled performance and the ways in which they allow these skills to be transferred between tasks. Despite the varied approaches, these theories offer credible explanations for changes in reaction time and accuracy in task performance typically observed with the practice of skills. Furthermore, they describe how automatic performance is achieved.

Debate exists regarding the relationship between these features of acquired skill over how the degree of automaticity affects the ability to transfer these skills. It is believed that the adaptability of skilled processes is governed by the extent to which a skill is or is not automatic. Some researchers suggest the increased efficiency of cognitive processes that develop with greater degrees of automaticity, facilitate skill transfer while others propose the nature of automatic mechanisms are too inflexible and may even hinder performance on a transfer task. The following literature review

presents detailed descriptions of the theories of skill acquisition, the mechanisms of automaticity, and describes the ways in which they affect the ability to transfer skill. The effects of differing degrees of automatic performance on skill transfer were explored in the current experiment.

Adaptive Control of Thought Theory

The ACT family of theories represents a successive series of increasingly precise models concerning human cognition. Anderson's approach to skill acquisition is based on a procedural model in which the underlying cognitive procedures that govern task execution are refined and strengthened (Anderson, 1982). The ACT theory makes the distinction between declarative and procedural memory structures. Declarative memory is knowledge about various domains from which meaningful associations are made between task requirements and the facts an individual has in this store for the undertaking of a task (Anderson, 1987). Accumulation of experience provides a large database from which this type of memory can draw from and as such, allows for flexibility in its application (Anderson, 1992). This information is converted into implicit procedural knowledge and is stored as "IF-THEN" rule-type pairings that Anderson terms *productions* (Anderson, 1982). Each production has a set of conditions and actions (e.g, IF the traffic light is green THEN go) based in declarative memory and it is proposed that as practice of these procedures increases so too does their refinement and specificity to the particular task (Anderson, 1981, 1982, 1983). This leads to skilled behaviour.

Several researchers have developed stage-type frameworks to explain the cognitive shifts that occur in the process of learning and developing skills (Adams, 1971; Gentile, 1972; Vereijken, 1991) particularly in the realm of motor ability.

Anderson identified that skilled performance developed through a series of stages defined by the type of memory used and the transition between them (Anderson, 1987). Moreover, the now classic three stages of learning model outlined by Fitts (Fitts & Posner,1967) are encompassed in ACT* theory to explain the evolution of skill from simple and slow initial task execution to rapid skilled performance.

Fitts' first stage is the cognitive phase (Fitts & Posner, 1967), which is the equivalent to Anderson's declarative stage in ACT* theory (Anderson, 1987). This stage is characterised by the use of weak problem solving methods and general productions to interpret information and knowledge in its declarative form (Fitts & Posner, 1967). This takes place for the first few task attempts as instructions are learned and strategies are formulated based on general strategies that an individual already has knowledge of from past experience. This process involves considerable attentional resources and performance is slow and error prone (Fitts & Posner, 1967).

The associative phase is the second in the three stage learning model, and is where declarative knowledge transitions from declarative to procedural knowledge as production rules. Anderson refers to this process as the knowledge compilation stage (Anderson, 1987). In this stage the developed strategies are either strengthened or weakened depending on how successful or unsuccessful they are for performing the task (Fitts & Posner, 1967). This type of feedback process allows for the refinement of appropriate performance techniques and facilitates the development of stimulus responses to specific cues.

The third and final stage in Fitts' model is the autonomous stage where the formulated production rules are strengthened and applied with increased efficiency and less effort (Fitts & Posner, 1967). Anderson (1987) terms this as the procedural stage where characteristic increases in speed and accuracy are observed. In this final

stage cognitive processing becomes more efficient and less mentally demanding that in turn, allows for increased task execution speed (Fitts & Posner, 1967). With decreased demand on attentional resources, the rate of performance improvement slows as automaticity in skilled performance is approached.

Instance Theory

Logan presents a theory of acquisition in which a domain-specific knowledge base of separate representations, or instances, is formed through an accumulation of memories from exposure to a task (Logan, 1988). The theory states that initial task execution relies on a general algorithm to provide a solution to, or reach an objective in an activity. With every successful execution a separate episodic trace is stored in memory and as more of these instances are acquired, an increasing collection of memories is provided to draw upon for the completion of that particular task (i.e., remembering a past solution) (Logan, 1988). Logan proposes that increases in speed and accuracy seen in acquisition, is the outcome of modifying cognitive procedures from time consuming, multiple-step algorithmic techniques to the more efficient, single-step process of memory retrieval for the task (Moors & De Houwer, 2006).

Instance theory holds three main assumptions: obligatory coding, obligatory retrieval, and instance representation. The first assumption of obligatory encoding refers to the innate and unavoidable process for the coding of events or items into memory store (Logan, 1988). This is done when any amount of attention is given to stimulus, however the quality of the memory for the stimulus is dependent on the focus or degree of attending. Obligatory retrieval describes the activation of a memory trace initiated by attending to stimulus that has been previously stored. This occurs involuntarily and the success of retrieval depends on the initial quality of

previous encoding (Logan, 1988). The last assumption of instance representation supposes that each encounter with an event or item is encoded and retrieved as its own separate instance, even if an identical stimulus had been presented previously (Logan, 1988).

Though there are variations and discrepancies in the beliefs about the underlying mental pathways and processes that govern the acquisition of skill, previous research has found that extensive practice typically leads to faster, more stable reaction times for numerous tasks (Watson, 1993). The belief is that as practice of methods that successfully complete a task increases, the governing cognitive mechanisms become more established and the techniques used become more refined (Cohen & Poldrack, 2008). As such, the acquisition of a skill is often measured as a decrease in performance times and an increase in the accuracy achieved in a set exercise.

Power Law of Practice

Classic skill acquisition research typically uses stimulus-response activities in which performance times and accuracy are recorded. Varied and extensive investigation of skilled behaviour has produced the most widely replicated and best-known empirical result in this area, known as the Power Law of Practice (Heathcote, Brown, & Mewhort, 2000). This law states that mean reaction times decrease as a power function of the amount of practice (Ashby, Ennis, & Spiering, 2007). Among numerous examples, this power-function has been demonstrated for cigar rolling (Crossman, 1959), consistent mapping and varied mapping versions of memory search tasks (Strayer & Kramer, 1994), and air traffic control and coordination tasks (Ackerman, 1988). The phenomenon has been well replicated throughout research in

the domain of skill acquisition, which provides good support as one of psychology's few true laws.

When plotted, results for such tasks share a similar pattern characteristic of the Law. Early in practice there is considerable and rapid improvement that is illustrated by a dramatic decrease in reaction time over trials. As practice continues the rate of improvement slows and becomes more gradual (Lacey, 2007). Eventually performance reaches a more constant asymptotic level in which very little improvement is observed (Lacey, 2007). At this point performance is considered to have reached a type of optimum level that may be limited by factors such as perceptual-motor abilities, memory retrieval delays, and individual differences (Lacey, 2007).

Another characteristic of attaining aptitude in executing a task is the apparent reduction of capacity demands over practice (Brown & Carr, 1989). That is, when a new task is encountered an individual's initial mental processing is highly controlled, requires active attention, and their cognitive capacity is limited whilst attending to the activity (Strayer & Kramer, 1994). However, with increased practice the processes used to perform the task become more efficient or 'stronger' (Anderson, 1992), requiring less active attention and are therefore less capacity limiting (Strayer & Kramer, 1994). One description of the transition from unskilled to skilled performance that recognises this shift in mental demand distinguishes between "controlled" and "automatic" task execution (Watson, 1993).

Automaticity

Many theories of automatic performance or automaticity, describe its development as the result of time-consuming controlled processes being replaced by

more efficient cognitive methods (Deutsch, Gawronski, & Strack, 2006). For example, Logan's (1988) Instance theory of automaticity describes a cognitive model of expertise that assumes that when a skilled behaviour is engaged there is a mental race between accessing the procedures for an algorithmic computation method for completing the task, and the recall of a previous instance in which the activity was successfully executed (Ashby, Ennis, & Spiering, 2007; Lassaline & Logan, 1993). The resulting act of performing the task relies on whichever mental technique 'wins' the race. However as more instances are created, the retrieval of a memory is believed to eventually dominate as the method used in skilled or automatic behaviour (Logan, 1988).

These outcomes demonstrate an ability to achieve rapid and constant task execution regardless of task complexity. For instance, in research conducted by Lassaline and Logan (1993) a counting task was used that displayed varying numbers of asterisks (6 - 11) on a computer screen. These displays were shown to subjects who were required to count and respond to the stimulus by selecting a button on a response pad that indicated how many items were in the display. As postulated by skill acquisition theories, initial task performance was slow as primary methods used to generate a response saw the participants having to attend to every item individually (Lassaline & Logan, 1993). Time taken to distinguish and tally single items has an additive effect. Therefore, as the number of items increased so too did response times. Lassaline and Logan (1993) postulated that if automaticity is obtained with practice in the counting task then performance should become based entirely on memory retrieval. That is, it should take no longer to respond to a pattern containing eleven elements than to a pattern containing six items. As such the slopes of the function relating response latency to numerosity should be flat.

Reaction times were plotted as a function of the number of items in each display to assess developments in processing techniques over the duration of trials. Automatic performance is characterised by a slope in plotted reaction times that indicate initial controlled attending to single items or steps in the task developing to stable performance times despite the complexity of the task (Deutsch, Gawronski, & Strack, 2006). Lassaline and Logan's (1993) experiment demonstrated that as practice of the task continued performance times did become less varied, indicating a shift in processing from the deliberate attention to single items to more efficient cognitive methods (Lassaline & Logan, 1993). They concluded that the participant's final performance illustrated mental processing techniques shifted from counting every individual item to a memory retrieval approach by recognition of the stimulus displays and their corresponding answer. The transition to more efficient methods accounted for the change observed in the reaction time data.

Another definition of automaticity considers the mental demand of skilled behaviour in terms of when skill-learning progresses with practice to the point at which an individual no longer requires focussed attentional control to carry out the activity (Beilock, Bertenthal, Hoerger, & Carr, 2008). It has been said that as the component mental processes become more automatic, there is an enhancement in the extraction of perceptual and cognitive information needed to execute the activity, which in turn increases proficiency (Strayer & Kramer, 1994). In an experimental capacity, automaticity can be defined in terms of mental or performance dual-task costs (Cohen & Poldrack, 2008). That is to say, while initial performance on a novel task is compromised by a concurrent secondary task, practiced skills can take place without performance costs (Logan, 1979; Posner & Snyder, 1975, as cited by Cohen & Poldrack, 2008).

Regardless of the lack of agreement regarding the underlying cognitive architecture of skill acquisition and automatic processing, it is well documented that with increased practice the time an individual takes to accurately perform practiced tasks will reduce (Deutsch, Gawronski, & Strack, 2006). Furthermore, given such proficient mechanisms that govern skilled performance, the power functions that illustrate performance improvement in skill acquisition are expected to predict continued improvements on these skills when they are performed in a new task (Speelman & Kirsner, 2001). This is known as skill transfer.

Skill Transfer

Transfer is the amount of influence the learning of one skill has on the learning of another skill (Hays, 2006). This influence can flow from a positive, negative, or neutral direction. Positive transfer occurs when skills learned in a previous task can be applied or assist in the acquisition of skills in a new task (Brown & Carr, 1989). It has been reported that positive transfer should occur by practicing skills that are cognitively similar. The more similar the cognitive processing characteristics utilized from the initially learned skill to the new skill, the more positive the transfer (Proctor, et al., 1991). Negative transfer is the opposite in that previously learned skills might hinder performance in a secondary task. Negative transfer may occur for several reasons such as when a previously acquired method for accomplishing a task transfers to a new task but results in a less efficient solution than if the new task had been learned on its own (Rehder, 2001). It may also occur when the presence of one, usually highly practiced, skill interferes with the execution of another, or when productions (ACT theory) that are effective for one task are ineffective in a transfer task and produce incorrect results when used (Rehder, 2001).

Neutral or zero transfer is a case in which a previously learned skill has no effect on a transfer task (Hays, 2006).

It makes logical and empirical sense that skill transfer is more likely to occur for tasks that utilise the same underlying abilities acquired at skilled performance levels than for tasks that do not share such skills (Ackerman, 1990). Lassaline and Logan (1993) concluded that if automaticity is obtained with practice in their counting task then performance should become based entirely on the faster and more efficient method of memory retrieval. As such, if these instances were included in a similar but new task it would be expected that performance on those familiar items would remain at the levels achieved in the initial task. Moreover, if a transfer task employs a skill acquired on an initial training task it could be assumed that performance would continue to improve as predicted by the practice function of learning observed in the training task.

In contrast, automaticity has also been described as being hard to modify once initiated (Strayer & Kramer, 1994) and difficult to inhibit (Deutsch, Gawronski, & Strack, 2006). It has been postulated that once learned, a skilled response becomes stored relatively permanently (Rehder, 2001) and due to the efficiency and immediacy of cognitive processing, the behaviour is then hard to suppress, modify, or ignore once activated (Cohen & Poldrack, 2008). As mentioned earlier, automatic responses are associated with little active attention or control and therefore have the potential to operate despite an individual's intentions (Strayer & Kramer, 1994). As such, the long-term memory for cognitive skills are liable to compromise performance in task execution as attempts to learn new responses to old stimuli will be plagued by persistent intrusion errors (Rehder, 2001).

A well-researched and well-used example of this phenomenon is that of the Stroop task (Cohen & Poldrack, 2008). This activity requires participants to name the colour of the text in which colour names are written. For example, if the word GREEN were printed in the colour YELLOW, the correct response from the participant would be to say "yellow". Numerous replications of this task demonstrate that subjects have considerable difficulty in controlling the impulse to read the word and often have trouble inhibiting their response to say the word when they respond with an answer (Cohen & Poldrack, 2008). This is known as the Stroop Effect and demonstrates how the well-practiced, automatic skill of reading can interfere with task performance.

Similarly, Treisman, Vieira, and Hayes (1992) found that after becoming automatized on a visual search activity, participant performance was enhanced by the introduction of extraneous stimuli if they were consistent with the initial training activity. However, performance was weakened if the stimulus were inconsistent with the task, as assessed by speed and accuracy (Treisman et al., 1992). They surmised that the learned automatic response to the search task affected performance, as the impulse to attend to irrelevant stimuli could not be controlled (Treisman, Vieira, & Hayes, 1992). Experiments such as these suggest that the more automatic a skill becomes the less flexibility there is to alter a skilled response. If so this may prove to be more restrictive on skill transfer. That is to say, with increased automaticity the ability to transfer a skill may decrease.

In a type of compromise between these suggested opposing outcomes of automaticity and skill transfer, there may be particular phases during the development of skill acquisition that are more susceptible to the influence of transfer than others. The implication is that as a skill becomes more automatic there may be a point at

which it is sufficiently learned for proficient execution of a task but flexible enough to be effectively adapted to a new task (Berryhill, 2006).

In support of this belief, Ackerman (1990) offers a dynamic perspective of skill acquisition and skill transfer that describes changes in the determinants of task performance and transfer potential at various stages of skill acquisition. This view considers that training and transfer situation can be distinguished into those that allow for same-stage transfer or for different-stage transfer. It is proposed that there is versatility in skill transfer depending on the ability to perform the task (Ackerman, 1990). Ackerman (1990) posits that there may be general abilities necessary to perform both training and transfer tasks in the initial stages of skill acquisition, but as skills become refined there are junctures at which abilities will allow for and determine optimum skill transfer.

The Current Study

Though much of the previous research in this area suggests there may be a relationship between automaticity and skill transfer there is clearly variation in conclusions about *how* automaticity affects the ability to transfer an acquired skill. There is an extensive wealth of research into how automatic skilled responses affect the ability to transfer that skill to a follow up task, however it is unclear how the degree of skill acquisition impacts on skill transfer potential. As such, the gap in the research prompts the question of whether the degree of automaticity can predict the transferability of a skill.

It is in the interest of answering this question that takes the focus of the current investigation. The experimental design allowed for comparisons between extent of automatic performance, regulated by varied lengths of experiment trials between

groups (practice), and also what effect amount of practice had on the ability to transfer skills from one task to another. In particular, the experiment was designed to look at the extent to which participants became automatised during the training phase and whether a relationship could be found to provide a basis on which to predict the amount of transfer that would take place from training to transfer.

The experiment was divided into two phases: training and transfer. Three versions of the training phase differed by varying lengths whilst the transfer phase was consistent across all versions. Participants were required to count a number of stars presented to them on a computer screen and discern whether the number of stars was odd or even, to which their response times and selected answers were recorded. The arrangements were presented in random order but were repeated throughout the experiment. The repetitious nature of the task exposed the participants to all the displays numerous and equal times, increasing their familiarity with the configurations with each exposure.

The transfer phase used identical displays from the training phase that alternated with additional arrangements that included extra star items. As such, the experiment was designed to observe and compare reaction times on the original displays from training to transfer phases.

Considering the nature of the task, The ACT* theory would predict that initial methods used to count the items would utilize a participants knowledge and abilities concerning how to add numerous items and their understanding of odd and even figures (Anderson, 1981, 1983, 1996). As practice increased, they would develop techniques that made addition more efficient by compressing the steps they take to reach an answer into fewer stages. For example, rather than attending to each item and tallying them individually, counting by twos or threes would offer a faster solution.

Instance theory for this task would speculate that initial performance would use primary algorithmic methods to count the items and arrive at an answer (Logan, 1988) similar to those methods in ACT*. As the displays are repeated however, memory instances for each of the displays should accumulate in the participant's memory store. With each exposure the memory traces become more numerous and access to an instance offers a faster solution to the task over controlled counting. That is to say, the participant would begin to remember the arrangements and associate their chosen response with each design.

As the Power Law of Practice demonstrates, faster more accurate performance is observed with increased practice. As such, it would be expected that the differences in the lengths of each of the training phases would result in different degrees of performance. That is, those who complete the longest of the trial blocks should reach faster reaction times by the end of the training phase compared to those in the second longest or shortest of the three experiments. The same would be expected for the second longest training phase over the shortest. That is to say, those who complete more trials are expected to become more automatic at the task over those who complete fewer. Moreover, it would be expected that reaction times to the original training phase displays that appear in the transfer phase will yield consistent or improved response performance due to the participant's previous exposure and practice to those arrangements.

Because of the high similarity between the training and transfer tasks, it would be expected that effective transfer should occur, as similar cognitive processes would be used. However, variation in theories of skill transfer offers several possibilities for the outcome of this experiment. For example, due to the varied lengths of the task it may be predicted that with more practice the participant has more opportunity to

acquire and refine efficient techniques suitable for transfer. As such it may be expected that those who complete longer training phases will display greater transfer over those who experience less trials.

Alternatively, if participants become exceptionally automatic in task execution their ability (or inability) to inhibit or alter their impulse on transfer displays. Because transfer displays include previously seen configurations (plus additional stars) this may impact their response accuracy or performance as the effort to stall their response and reassess the array may cost them time. As such it might be expected that those who complete more blocks become more automatic and display poorer transfer than those who complete fewer trials in the training phases.

A third possibility offered by the research is a type of optimal amount of training that facilitates the greatest transfer. It suggests that with too little training, skills may not be sufficiently acquired or refined enough for them to be useful in a transfer task. However if they are too automatic they may be too specific to the task for which they were learned to allow their application in a differing context. It is suggested then that there is a mid range in which abilities and processes developed for task execution have developed sufficiently enough for competent execution but underlying cognitive processes remain relatively flexible and can accommodate moderate changes in the task. That is to say, potential for skill transfer is at its most favourable. If this is the case, it may be observed that the participants who complete the experiment with the second most number if training trials (mid range) would show the greatest degree of transfer to the transfer phase, compared to the other two groups.

Due to the scope in opinion and research within this area, rather than begin with a hypothesis of predicted outcomes, this research aimed to explore the nature of automaticity and how it relates to skill transfer. By using a simple task that could

provide sufficient and manageable results it was believed reliable outcomes would be produced and allow sound conclusions to be drawn. By comparing differences in reaction times and extent of transfer as a function of the amount of training, the experiment was designed to assess whether the degree of automaticity could predict transfer of a skill.

Method

Research Design

A quantitative research design was used to determine the differences in skill transfer performance on a computer-generated counting task. The experiment involved recording response times and accuracy to a visual display task that included initial training phase trials and transfer phase trials. Three groups of participants were required to complete a training phase that differed by the number of trial blocks; 10 blocks, 20 blocks, and 30 blocks. Each block consisted of eight displays of visual configurations that varied in the number from 6 to 13 items. Following the training phases, all groups completed the same transfer phase that consisted of an additional 2 blocks. Presentation of the displays was random and no configuration was presented more than once in each block.

The task involved displaying a series of star arrangements on the computer screen with the predetermined number of blocks of trials assigned to each of the three groups for training. The task required the participants to determine the number of stars presented on the screen and discern whether that number was an odd or even amount. They indicated their answer by pressing one of two buttons on a response pad that corresponded to the appropriate "ODD" or "EVEN" answer.

The transfer stimuli were produced using the identical stimulus configurations from the training phase with the addition of a number of red stars to each stimulus. The additional stars varied in number from 1 to 4 and transfer displays remained consistent (i.e., the 6 star training stimulus display always had an additional 4 red stars in the transfer stimuli, and in the same item arrangement, etc.). Each training stimulus had a corresponding transfer stimulus that was shown directly following the presentation of and response to the original training stimuli. Participants were instructed to respond as they did in the training phase by including the red stars to the count of black stars.

Participants did not receive any feedback on their responses and the experiment continued regardless of whether their indicated answer was correct or not. Selected responses and reaction times were recorded for all trials. Furthermore, poor performance (i.e. response accuracy of 50% or less) may have indicated guessing or a misunderstanding of the task requirements and results were screened for incorrect responses to ensure the task was correctly and effectively completed. No participants were removed for poor performance.

All aspects of the experimental design and procedures used in this research met the relevant guidelines contained in the National Statement on Ethical Conduct in Human Research, the Australian Code for Conducting Responsible Research, and the ECU Policy for the Conduct of Ethical Human Research and was granted ethics approval by the Faculty of Computing, Health and Science Ethics Committee.

Participants

In total, 60 participants were tested with 20 in each experimental condition. Participants were sought from Edith Cowan University student population via poster

and flyer requests, announcements during lectures, and email contact for those listed on the Edith Cowan University School of Psychology and Social Science participant register, and were recruited following responses of interest to participate. Additional participants were recruited from the general public on inquiry and request. All who participated received an information letter outlining the study (Appendix A), an instruction sheet explaining how to complete the task (Appendix B), and a consent form that was completed before the commencement of the experiment (Appendix C).

A total of 62 participants completed the experiment, all of whom were 18 years or older. Results from 2 participants were selected at random and excluded due to surplus numbers in the 10 block task. The sample size was considered reasonable to obtain and produce a manageable but sufficient amount of data.

Materials

A computer-generated task was programmed using the Superlab computer program for the training and transfer visual counting tasks. The program and computer were obtained from Edith Cowan University's psychology department at the Joondalup campus. The displays were shown on a computer monitor and participants indicated their answers by pressing buttons on a response box.

Trials were presented as blocks of eight different patterns comprised of black stars only in the training phase. Presentation order within blocks was random. This means that no item was repeated until all items within a block had been presented. These same patterns were used in the transfer phase with additional red stars added to the configuration after an initial odd/even response was made. Participants were required to respond again but this time taking the red stars into consideration for their answer.

Accuracy and reaction times were recorded by the Superlab program and analysed using Microsoft Excel and SPSS Version 17.0 in the computer lab at Edith Cowan University Joondalup campus.

Procedure

Three groups of 20 participants completed training and transfer trials of the computer generated star-counting task. The training trials varied in length between groups; Group 1 completing 80 trials in 10 blocks, Group 2 completing 160 trials in 20 blocks, and Group 3 completing 240 trials in 30 blocks, with each block containing eight trials. Following the practice trials, all participants completed the transfer phase trials of 16 trials in two blocks of eight trials each.

After instructions were given and any questions addressed, a 'Ready' screen was displayed on the computer monitor and, when they were prepared, participants commenced the task by pressing a "READY" button on the response pad. The trials began immediately following their indication. They were shown a series of star patterns randomly selected from a possible eight configurations containing 6-13 stars. Half of the configurations contained an odd number of stars and the other half contained an even number. The pattern remained on the display screen until a response was made on the response pad. Participants were required to indicate their answer by pressing one of two buttons labelled "ODD" or "EVEN". The eight configurations were presented repeatedly but in a random order throughout the training phase with no display appearing more than once in any one block.

In the transfer phase the eight arrangements from the training phase were shown again in a random order. In each transfer trial a stimulus was presented and participants responded as they did in training. Once they had indicated their

ODD/EVEN answer, additional red stars were added to the display on the screen. Participants were required once again, to count all stars to give an ODD/EVEN response for the new display. All participants were instructed to respond as accurately and as rapidly as possible throughout the task.

Three Honours students from Edith Cowan University conducted the research for the completion of their respective theses. Each contributed to the sourcing and recruitment of participants as well as running them through the experiment. Instructions given to each participant were standard among all primary researchers and all participants undertook the experiment in the same computing labs at Edith Cowan University, Joondalup campus to maintain consistency.

Due to an error in the programming of the experiment in the SuperLab computer program, complete results were obtained for only the 10 block and 30 block groups. As such, the 20 block trials were removed from analysis of results for the purpose of this research.

Results

Due to an error in the programming of the 20-block trial the data from this condition could not be used. As such, data from the 10-block and 30-block conditions only were used for the analyses performed for this research. All data screening and data analysis procedures were conducted using Statistical Package for the Social Sciences (SPSS) Version 17.0 and Microsoft Excel, Windows 7 Version.

The data was initially screened for each training phase (responses for 10 blocks of 8 stimuli for the 10-block condition, and responses of 30 blocks of 8 stimuli for the 30-block condition), and transfer phases (responses for 2 blocks of 16 stimuli) for incorrect results. All incorrect responses (i.e., response of "EVEN" when the number of items in the stimulus display was odd, and vice versa) were excluded prior to analyses. Furthermore, because the interest of this research is focused on the ability to transfer skills learned in an initial task (i.e., the counting stimulus displays) to a secondary task that utilizes the same skills (i.e., the identical stimulus displays), reaction times for the additional star displays with added red stars were also excluded from all analyses. That is, only performance on the initial part of each transfer trial was analysed; the stimuli equivalent to the training trials. No significant outliers were found in the results and as such, the obtained data was considered appropriate for the intended comparisons and analyses. Reaction times and accuracy were analyzed separately.

Accuracy

Analysis of the accuracy data was conducted for both the 10-block and 30-block groups using *t*-tests between the first training blocks and the final training blocks, and between the final training blocks and the first transfer blocks.

Examination of mean accuracy of the first training, final training, and first transfer blocks indicated a high level of accuracy was achieved during both experiment phases. Both groups achieved 90% accuracy in the first training block, which increased to 98% and 96% for the 10-block group and the 30-block group respectively in their final training blocks. Both groups demonstrated reduced accuracy in the first transfer block to 93% for the 10-block group and a marginal decrease to 95% for the 30-block group.

Results revealed that there was no statistical difference in accuracy scores for the 30-block group between the initial training and final training blocks. Nor was there any difference between the final training blocks and the first transfer blocks. Analyses of the 10-block group yielded significant differences in accuracy with an increase from the first training blocks and the final training blocks, but no statistical difference between final training and first transfer blocks. Further between *t*-test comparisons between first training, final training, and first transfer blocks from both 10-block group and 30-block group respectively, indicated no significant differences of performance accuracy between groups. The relevant output is included in Appendix D.

Reaction Time Performance

Comparisons between performance on initial training and final training blocks were conducted within and between both groups using *t*-tests. Performance was measured using mean reaction times (RT) of the correct trials in each block, measured in milliseconds (ms). Comparisons using these times from the first training, final training, and first transfer blocks were conducted within and between the groups to

determine if any reaction time performance differences developed over the duration of trials. These performance times are presented in Figure 1.

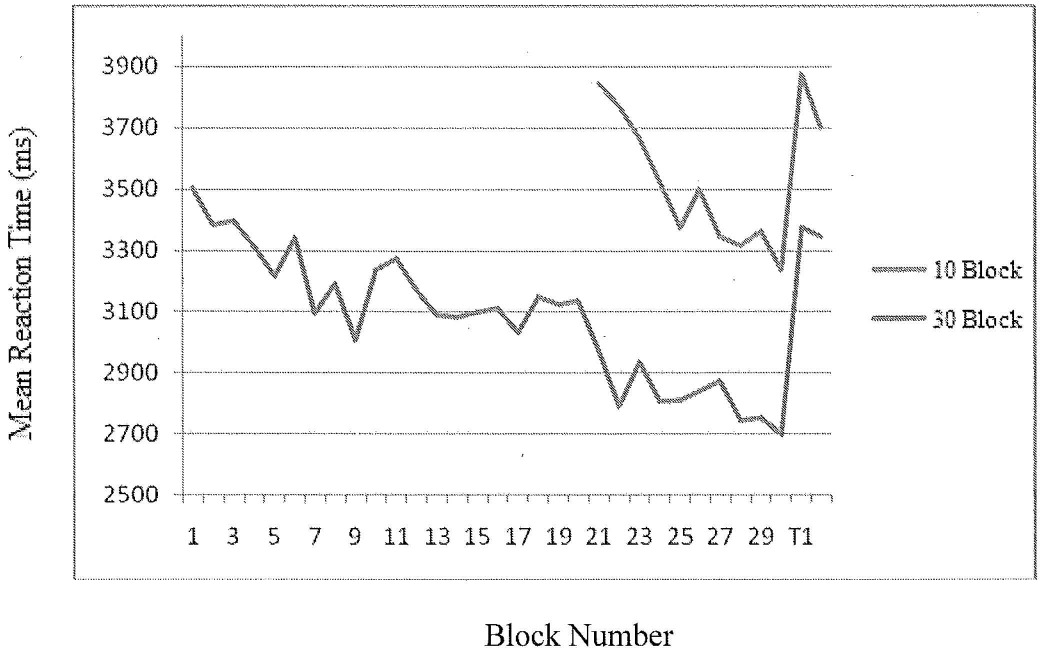

Figure 1. Mean reaction times during training and transfer for the two experimental conditions.

Comparison of mean reaction times between the first training block (M = 3847.21 ms, SD = 1117.80 ms) and the final training block (M = 3236.65 ms, SD = 849.79 ms), $t(19) = 4.26, p < 0.05$ for the 10-block group revealed a significant difference. There were also significant differences between the final training block (M = 3236.65 ms, SD = 849.79 ms) and the transfer block (M = 3828.20 ms, SD = 1235.13 ms), $t(19) = 4.55, p < 0.05$ for the 10-block group. Results for the same comparisons in the 30-block group indicated significant differences in reaction time from the initial training block (M = 3505.33 ms, SD = 942.47) and the 30th (final) training block (M = 2697.07 ms, SD = 611.16), $t(38) = 3.22, p < .05$. Differences were also significant between the final training block (M = 2697.07 ms, SD = 611.16) and

the first transfer block (*M* = 3373.74 ms, *SD* = 767.53), $t(38) = 3.08$, $p < .05$, for the 30-block group.

Comparisons between the groups on comparable blocks indicated no statistical difference between the first training blocks or the transfer blocks, however did reveal a difference between final training of the 10-block group (*M* = 3236.65 ms, *SD* = 849.79 ms) and the 30-block group (*M* = 2697.07 ms, *SD* = 611.16), $t(38) = 2.31$, $p < .05$. The absence of a statistical difference between the first training blocks between groups indicated that all groups performed at a similar level during initial training. These results suggest that all participants performed at a similar level initially but extended practice facilitated participant's ability to complete the task at a faster rate. Descriptive statistics for the reaction times of the blocks are presented in Table 1 and relevant summary tables are presented in Appendix E.

Table 1

Comparisons of Mean Reaction Times (ms) During First Blocks, Final Blocks, and First Transfer Blocks.

	Condition			
	10 Block		30 Block	
Block	M	SD	M	SD
First Training	3847.21	1117.80	3505.33	942.47
Final Training	3236.65	849.79	2697.07	136.66
First Transfer	3828.20	1235.13	3373.74	171.62

Transfer Disruption

Differences in reaction times from final training blocks to the initial transfer blocks indicate disruption in task performance due to the change in task. The

magnitude of the disruption was calculated by simple subtraction of the final training phase block RTs from the first transfer block RTs for each participant. These values were compared between groups using an independent groups *t*-test. Results indicated that whilst there was more disruption on average seen in the 30-block group (M = 676.67 ms, SD = 520.5) the difference was not statistically different to the average disruption of the 10-block group (M = 591.55 ms, SD = 581.76), $t(38) = .629$, $p > .05$. A table for the differences in reaction times for each participant from the final training blocks to the first transfer blocks are presented in Appendix F.

Regression Analysis

Linear regression analyses were conducted for each participant using RT scores as a function of the number of star items in each stimulus. This was done for both the 10-block and 30-block groups by combining the results from the first two training blocks (i.e. blocks 1 and 2 for the 10-block group and blocks 1 and 2 for the 30-block group) and combining results from the last two training blocks (i.e. blocks 9 and 10 for the 10-block group and blocks 29 and 30 for the 30-block group), to determine if any changes occurred in reaction times by number of items over practice. As part of the initial screening process in which incorrect responses were eliminated, not all blocks had complete data for all 8 stimuli. As such, only RT scores that had response values for stimulus with the same number of items from each block (e.g., 6 star stimulus from block 1 and 6 star stimulus from block 2, etc) were used in the analysis. Those that did not have corresponding output from both blocks were excluded from the analysis. The reason for using data from two blocks of trials to perform this analysis, rather than just one block was that more data points would enable a more reliable estimate of the relationship between RT and the number of

stars in a stimulus. As such, between 8 and 16 figures were used in each linear regression analysis after the deletion of incomplete pairs.

According to theories of skill acquisition, initial task performance is slow because primary methods used to generate a response involve controlled attending and numerous steps. In this experiment, this feature would refer to the need for participant's having to attend to every star item individually and add them one by one. As previously mentioned, the time taken to discriminate then tally single items has an additive effect meaning that the more numerous the stars in the presented stimuli, the longer the reaction time will be. However, as practice continues and automaticity is approached, performance should become based entirely more efficient and less time consuming methods. This implies that it should take no longer to respond to a stimulus containing 13 stars than to a stimulus containing 6 stars.

The linear regression analyses provided functions for each participant for their response times as a function of the number of stars. These equations took the form of $RT = m\mathrm{x} + c$, where m indicates the degree of angle, or slope in the plotted line, x corresponds to the number of stars, and c is the constant. As predicted by afore mentioned features of improvement in cognitive mechanisms of skill acquisition, the slopes (m) of the functions relating response latency to numerosity would be to expect to reduce with practice.

T-test comparisons of slope (m) values were conducted between first and final blocks within groups to investigate and any differences over the course of the experiment. Respective first blocks and respective final blocks between groups were also compared to examine differences over the varied training lengths. No statistically significant differences were found.

Once all m values were obtained, Pearson's correlations were carried out comparing the m value with the disruption from the final training block to the first transfer block for each participant. Results indicated a non-significant correlation for the 30-block participants, $r = 0.14$, $n = 20$, $p = 0.56$, while a significant, positive correlation was obtained for the 10-block participants, $r = 0.50$, $n = 20$, $p = 0.01$. This indicates that, although there was more variation in the range of the disruption figures for the 10-block group, there were more participants for whom there was limited (not significant) disruption between final training and initial transfer, as indicated by performance time differences. In the 30-block group, nearly every participant showed a disruption. This is consistent with the correlation data in that the 10-block group, those who did not show a disruption tended to be those with small slope values, whereas this relationship was not so apparent in the 30-block group. As such, although there is a vague suggestion of the 30-block group having lower slopes than the 10-block group in the final training block, and hence being closer to automaticity, they also showed a greater likelihood of being disrupted in the transfer phase. A table of slope (m) values and constant (c) values for all participants and correlation summary table are presented in Appendix G.

Discussion

This experiment was designed to explore the relationship between automaticity and skill transfer. That is, whether the degree to which a skill becomes automatic can provide some indication of how well these skills could be transferred to a different yet similar task. Outcomes of the experiment used for the investigation provide varied support for the diverse aspects of skill acquisition, automaticity and skill transfer.

Comparison of mean reaction times between the initial training blocks of both groups indicated that all participants performed at a comparable level early in the task. Both groups showed significantly faster performance times in the final training blocks compared to the initial training blocks. Moreover, the group who received the greatest amount of training were observed to perform significantly faster than those who had less training by the end of the training phase. The latter results indicate that more practice resulted in significant improvements as it allowed participants to refine their skill and perform at a faster rate. Taken together, these outcomes indicate that improvement was a direct result of increased performance rather than differences in ability.

These effects are predicted by and provide support for theories of skill acquisition. These theories describe the improvements in performance on skilled task as the result of changes in the efficiency of underlying cognitive mechanisms, which is facilitated by practice. For instance, theories of ACT (Anderson, 1982) suggest that initial techniques employed in task execution use several rule-based steps to produce successful task execution. As the steps are repeated with practice these productions are refined and compressed into fewer, more efficient cognitive processes. It is plausible that in the course of this experiment this may have occurred as a shift from

the counting of every item individually early in the task to a process of grouping items together in a process known as subitizing (Lixia He & Tiangang Zhou, 2009).

This innate phenomenon is the ability to appreciate a number of items presented in an individual's field of view without having to attend (count) to every item individually. As the upper limit of subitizing is typically found to be approximately 5 items (Lassaline & Logan, 1993), the least number of stars contained in any one stimulus in the designed experiment was 6. This ensured some counting was necessary and was performed by the participants. It is possible however that the stimuli were divided into smaller numbers of items within the patterns stimulus via the subitizing process. For example, the elements in the 12 star displays may have been differentiated into subgroups containing three or four stars. Such a process would require less time than serially counting every item in the stimulus as the participant need only total three or four figures to produce an answer. Essentially this reduces the number of steps required to complete the task. With practice these processes become more refined, require less cognitive control and in turn, reduce performance time.

Applying Instance theory to the experiment outcomes would focus on the effect of practice as a process of creating memories, or instances. Although initial techniques for completing the task would use multiple step algorithms, repeated exposure to each stimulus creates a separate memory, which is then stored as an individual instance. As instances accumulate they offer an increasing number of memories available for single step retrieval. Ultimately the production of responses to a task is determined by a race between the algorithm and the remembering of an instance. For this experiment, this implies that participants initially used counting methods that required them to attend to each star in the stimulus and produce an

answer by addition. However, due to the repetitive nature of the task, a memory would have been created for each of the stimuli every time they were encountered. As such, with increased practice a cognitive shift from controlled addition methods to rapid memory retrieval for the stimulus pattern and its corresponding answer, would account for the decrease in performance times.

Research suggests that the ability to transfer a skill acquired in one task to a different but similar task is more successful if the tasks require similar cognitive methods for their successful execution. As such, because of the considerable likeness between the training and transfer tasks, it would be expected that the techniques acquired in the training phase would benefit performance in transfer. Due to insignificant differences found between first training and transfer blocks for both the conditions, results are problematic for theories of skill acquisition.

For example, ACT* theory states that increased practice refines and compresses cognitive steps used for task execution, making the method faster and more efficient. Since the transfer phase contained similar stimuli from the training phase and the objective of the task was identical, it could be expected that transfer task would utilize the same techniques (if proficient skill was acquired in training). Furthermore, if the processes of Instance theory governed performance, aptitude gained in the training phase would suggest a benefit to performance on the same stimulus presented in the transfer phase. Therefore, theories of skill acquisition would predict at least equal reaction times to those achieved in training on training phase stimulus, or improvement with continued practice as predicted by the Power Law of Practice.

Increased practice refines the cognitive methods of skill acquisition not only by improving their efficiency but also reducing mental demand. As such, these results

may be better explained by considering the extent of practice. Some researchers suggest the increased efficiency of the mechanisms of automatic methods benefit performance on different yet similar tasks if they can utilize the same underlying techniques. That is, if automaticity is attained for a skill, the speed and efficiency of processing should be consistent if the same techniques are used in different circumstances from which the skill was initially acquired. Others suggest that the more automatic a skill becomes the less ability there is to adapt to changes in task. The view is that automatic cognitive methods become specific to the task for which they were acquired. Moreover, the nature of automaticity makes responses difficult to control and inhibit and may stall task performance if automatic responses are triggered in a task they are not appropriate for. A third alternative suggests an optimum level along the development of automatic performance exists in which transfer can take place. This describes circumstances in which a skill is sufficiently learned for proficient task execution yet flexible enough to accommodate some variation.

The apparent lack of transfer observed in the outcomes may be better understood by taking into consideration these differing views of automaticity. It is suggested that the 10-block group did not receive enough practice to have acquired significant automatic ability in task execution. Moreover, the 30-block group, having achieved significantly faster performance times over the duration of their training, achieved a greater degree of automaticity. The lack of transfer as a result of automatic performance is due then, to the inability to effectively adapt techniques for the changes in task. This is also described as transfer disruption, which is the cost on performance when a change is experience in a task. That is to say, although training and transfer shared many similarities in between the stimuli, cognitive mechanisms

developed in the training task became too specific to apply to the variation in the transfer phase.

Regression analysis provided illustration of changes in cognitive techniques for task completion. According to the theory, improved efficiency of cognitive methods would predict modifications in function that would allow performance to show no difference in reaction time despite the numerosity of items. Observation of reaction time means between first and final blocks training of both groups did reveal that participants showed less variation in performance times as a function of the number of items. Furthermore, the group that completed more training achieved less variation again, regardless of number of stars in the stimuli compared to the other, less practiced group. However, none of these differences proved statistically significant. For true validation that automaticity had been achieved for the task, outcomes for the linear functions determined by the final training blocks would show no significant variation in slope (*m*) despite the number of presented stars.

Correlations between slope (*m*) values obtained in the regression analysis, and transfer disruption demonstrated a significant positive correlation for the 10-block group. Outcomes illustrated that although there was more variation in the range of the disruption figures, there were less instances of disruption between final training and initial transfer, as indicated by performance time differences. The 30-block group yielded no significant correlation as nearly every participant appeared to be affected by transfer disruption. This is consistent with the correlation data in that the 10-block group as those who did not show a disruption tended to have small slope (*m*) values, whereas this relationship was less evident in the 30-block group. As such, although there is a vague suggestion of those who received extended practice achieving greater automaticity, as indicated by lower slopes in the final training block than the group

who received less training, they also displayed a greater likelihood of being disrupted in the transfer phase.

This is consistent with the views of automaticity described earlier. Although the results suggest neither group became completely automatic in performance, the group who had greater practice became significantly faster overall by the final training phase (i.e., closer to automatic performance). The 30-block group also demonstrated significantly slower performance from the final training to initial transfer stage than did the less practiced group. As mentioned, this is assumed to be the result of cognitive methods having less flexibility to adapt to moderate changes in task. Therefore, participants had difficulty in applying the techniques learned in the training phase to the transfer phase and took added time to process and respond to the new task, indicated by performance times. The significant correlation between those who received less training indicates they sustained performance levels from training to transfer by reactions time despite the change in task.

Due to the initial the observations that both groups began to show less variation in responses regardless of the numerosity of stimuli, and the 30-block group continued to level beyond that achieved by the 10-block group, it is reasonable to suggest that with continued practice slopes would have continued to even out until there was no significant difference in performance (variation) between stimulus displays. As such it may be concluded in this instance, that insufficient practice was provided to achieve the efficiency required to process the stimuli at an optimum level achieved with true automaticity. It also implies that with these performance improvements there is a greater possibility that changes in task will see greater transfer disruption.

Limitations and Future Research

Previous research supports outcomes of this experiment and assists in rationalising the conclusions of the investigation. However, due to restrictions in the data there is room for further investigation in this area. Firstly, the loss of data due to an error in the programming of the experiment meant that a mid-range for training practice was eliminated from the original design. Though the data that was generated provided valuable information on the relationship between the extremes in the scope of the experiment, the inclusion of an average position in the outcomes would have enriched conclusions about the development of automatic skill and the implications for skill transfer.

Furthermore, correlation analyses between linear slope and transfer disruption suggests that more training is required to benefit clarity in results. Output suggest that although variation in performance as a function of the number of stars in the stimulus decreased, the analysis from initial to final blocks training showed no *significant* difference in this performance. This demonstrates that whilst automatic performance began to develop, high performance levels, which would indicate attainment of true automaticity, were not achieved. The inclusion of another group with a greater number of blocks in the training phase would be expected to allow them to develop a greater degree of automaticity. This information could enhance the outcomes by providing information on how processing closer to automaticity effects transfer.

Another potential limitation to the study regards the individual aspects of the participants. The selection process for recruiting participants was random; however personal features of those involved that may have had some effect on results were unaccounted for. Though the experiment conducted in this research was a relatively simple one, participants were not screened for any possible conditions that may have

influenced their performance. For example, varying visual abilities (e.g., visual dyslexia) or other attention disorders that which may have affected their ability to process the stimuli in the manner it was presented, or compromised concentration. Additionally, age was not recorded or accounted for in the task. Previous studies that have focussed on skill acquisition and age have revealed age-related differences in ability to acquire and transfer skill (Ho & Scialfa, 2002). Though it is not believed these factors significantly affected results or compromised outcomes, controlling for these potential variations would be suggested on replication of this study.

Conclusions

These findings explore the relationship between varying degrees of automaticity and how it affects the ability to transfer acquired skill. Results of this research indicate a significant shift in flexibility of cognitive processes over the development of automatic performance. Debate exists amongst research to the extent automatic performance benefits or hinders skill transfer. Some describe the efficiency of automatic techniques improves transfer if the cognitive processes are similar between tasks, whilst others believe automatic behaviour is too task specific, impulsive, and uncontrollable to transfer and costs performance ability.

This experiment highlights transfer performance at either end of a substantially differed level of skill acquirement. The results showed expected outcomes in improvement over the course of practice, and began to illustrate automatic behaviour by decreases in performance times despite the complexity of the task (number of stars). Observing transfer performance of the groups, the results support the notion that while limited practice restricts the opportunity to refine skills to an automatic level, there is greater consistency in task performance from training to

transfer. Furthermore, more extensive training facilitates faster performance, moving cognitive processes further toward automaticity. However greater efficiency and impedes on the success of skill transfer and increases susceptibility to transfer disruption.

Without a mid point from which to further compare automatic performance and degree of transfer between most to least practice, it is difficult to conclude whether there is in fact an optimum point at which transfer from one skill to another could take place. Despite the absence of this gauge, this research provides support for the opinion that greater degrees of automaticity predict poor transfer of skill whilst less allows flexibility in cognitive methods for transfer. As such these results propose it is possible to estimate the quality of transfer to the extent that increased automaticity has a limiting effect on skill transfer, whilst less results in more consistent performance from training to transfer tasks. It can be concluded then, that automaticity in skilled performance could be used to predict the success of skill transfer.

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Appendix A

Information Sheet

Thank you for your interest in this study. My name is Jana Melis and I am currently completing my Psychology (Honours) degree at Edith Cowan University Joondalup campus.

The aim of the proposed research is to investigate the area of skill acquisition and skill transfer using a simple counting activity.

Your participation will require you to complete a simple visual counting task. The task uses a computer program to display a series of star configurations that you will be required to count and determine whether there is an odd or even number of items. Pressing one of two corresponding computer keys for an "odd" or "even" answer will indicate your response.

The experiment involves two phases. Each phase is made of blocks of display trials. The number of blocks you receive in the training phase will be dependent on which group you are assigned to. Though there will be some variation in the length of the trials, the task is anticipated to take no more than an hour.

The rationale and design of this study has satisfied the guidelines laid down by the Edith Cowan University Ethics Committee. Results will be used solely for the purpose of this study. All data remains confidential and at no time will your name be reported. If you are interested in the outcome of this research, I will be pleased to share it with you upon completion of the project, which is scheduled for October 2010. Please see my contact details below.

If you are interested in participating in this research or would like further information, please contact me.

Tel: [redacted]
jmelis@student.ecu.edu.au
[redacted]

Yours sincerely,
Jana Melis

Appendix B

Thank you for your interest in and giving your time to participate in this research.

For this experiment you will be required to complete a simple counting task. A series of display screens will be shown to you with a number of stars on them. Your task is to count the stars on the screen and indicate whether there are an 'ODD' or 'EVEN' number of items by pressing the allocated buttons on the response pad.

To begin the task a "READY" screen will be displayed. Please press the TOP LEFT hand button on the response pad when you are ready to begin. The first display screen will appear immediately after your response.

If you determine the number of stars in the display to be an 'ODD' number, please indicate by pressing the BOTTOM LEFT button on the response pad marked "ODD".

If you determine the number of stars in the display to be an 'EVEN' number, please indicate by pressing the BOTTOM RIGHT button on the response pad marked "EVEN".

It is important for you to be as fast <u>and</u> accurate as possible.

At some point during the experiment, there will be a slight change in the display. However, your task remains unchanged. That is to say you must count ALL items in the display and respond 'ODD' or 'EVEN' accordingly.

Do you have any questions?

Please begin the experiment by pressing the "READY" button when you are ready to begin.

Appendix C

Consent Form

I______________________________ have read the information sheet provided and agree to participate in the research study to be conducted by Jana Melis of Edith Cowan University. I understand the requirements and nature of the study and am volunteering my participation. Any questions I have asked relating to the research have been answered to my satisfaction. I give the permission for the data to be used for the completion of a Psychology Honours degree and acknowledge that it may be published. I understand that my name and any additional personally identifying information will not be used.

Signed: Research Participant: ________________________ Date: _________

Contact Number(s): ______________________

Signed: Primary Researcher: _________________________ Date: _________

Appendix D

Accuracy Output Summary Tables.

t-test Summary Tables of Accuracy Score Comparisons Between First Block and Final Block for 10-Block Group

Paired Samples Test

		Paired Differences		
		Mean	Std. Deviation	Std. Error Mean
Pair 1	Block 1 – Block 10	-.65000	1.08942	.24360
Pair 2	Block 10 – Transfer 1	.40000	.88258	.19735

		Paired Differences		t	df	Sig. (2 tailed
		95% Confidence Interval of the Difference				
		Lower	Upper			
Pair 1	Block 1 – Block 10	-1.1598	-.14013	-2.668	19	.015
Pair 2	Block 10 – Transfer 1	-.01306	.81306	2.027	19	.057

Appendix E

Mean Reaction Time Output Summary Tables for 10-Block and 30-Block Groups.

t-test Summary Tables of Reaction Time Score Comparisons Between First Block and Final Block for 30-Block Group

Paired Samples Test

		Paired Differences		
		Mean	Std. Deviation	Std. Error Mean
Pair 1	Block 1 – Block 10	610.55923	640.34717	143.18598
Pair 2	Block 10 – Transfer 1	-591.55429	581.75565	130.08452

		Paired Differences		t	df	Sig. (2 tailed
		95% Confidence Interval of the Difference				
		Lower	Upper			
Pair 1	Block 1 – Block 10	310.86753	910.25093	4.264	19	.000
Pair 2	Block 10 – Transfer 1	-863.82431	-319.28426	-4.547	19	.000

t-test Summary Tables of Reaction Time Score Comparisons Between Final Block and First Transfer Block for 30-Block Group

Paired Samples Test

		Paired Differences		
		Mean	Std. Deviation	Std. Error Mean
Pair 1	Block 1 – Block 30	808.26601	1154.93218	258.25069
Pair 2	Block 30 – Transfer 1	-676.67250	520.50382	116.38819

		Paired Differences		t	df	Sig. (2 tailed
		95% Confidence Interval of the Difference				
		Lower	Upper			
Pair 1	Block 1 – Block 30	267.74112	1348.7909	3.130	19	.006
Pair 2	Block 30 – Transfer 1	-920.27579	-433.06921	-5.814	19	.000

t-test Summary Tables of Reaction Time Score Comparisons Between First Transfer Block for 10- Block Group and First Transfer Block for 30-Block Group

Paired Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	df
Mean RT	Equal variances assumed	3.036	.090	2.305	38
	Equal variances not assumed			2.305	34.506

		t-test for Equality of Means				
					95% Confidence Interval of the Difference	
		Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Mean RT	Equal variances assumed	.027	539.58000	234.05814	65.75407	1013.4059
	Equal variances not assumed	.027	539.58000	234.05814	64.17355	10149864

Appendix F

Summary Table for Final Block Mean Reaction Times, Transfer Block Mean Reaction Times, and Disruption

Summary Table for 10-Block and 30-Block Final Training Block, First Transfer Block, and the Disruption in Reaction Times

	Block 10			Block 30		
	Final	Transfer 1	Disruption	Final	Transfer 1	Disruption
1	2770.75	3351.6	580.875	3001.375	3339.286	337.911
2	3626.43	3892	265.5714	2551	2639.286	88.286
3	4416.25	4947.1	530.8929	2032.571	3053.375	1020.804
4	2789.5	3001.6	212.0714	2673.25	4446.25	1773.000
5	4491.5	6360.3	1868.75	2958.625	3783.25	824.625
6	3447.67	4530.7	1083.048	2913.75	3605.25	691.500
7	3928.13	3828.8	-99.325	3412.429	4277.429	865.000
8	3017.75	3511.9	494.1071	2367.25	2403.125	35.875
9	2310	2728.3	418.25	2609.286	3775.5	1166.214
10	3810.25	3804.5	-5.75	3114	4072.429	958.429
11	3775.29	4891.1	1115.857	3108	2933.125	-174.875
12	2305.5	2460.6	155.125	4342.375	5271.5	929.125
13	2902.38	2949.9	47.48214	2355.857	2823.2	467.343
14	3374.43	3691.2	316.7381	1968.857	2301.286	332.429
15	3180.13	4543	1362.875	2815	3130.875	315.875
16	2942.5	4399.6	1457.071	2734.75	3182.5	447.750
17	2334.88	2386.3	51.41071	2436.571	2514.625	78.054
18	2133	2296.6	163.625	2089.125	2835.25	746.125
19	5132.88	6575.8	1442.875	1451.143	3131.625	1680.482
20	2043.75	2413.3	369.5357	3006.125	3955.625	949.500

Appendix G

Slope (m) and Constant (c) Value Tables for the Linear Regression Analysis

Summary Table for the 10-Block Linear Regression Analysis of Combined Blocks 1 & 2 and Blocks 9 & 10

Subject	Blocks 1 and 2		Blocks 9 and 10	
	Constant	m	Constant	m
1	74.446	313.125	-8.893	290.607
2	1003.351	279.601	445.791	338.166
3	245.625	510.750	-3220.976	760.274
4	-1504.107	480.268	-335.220	340.280
5	1773.943	377.271	-2742.095	776.780
6	-1019.692	560.558	37.495	404.926
7	5682.534	-91.593	1878.948	177.514
8	1692.505	241.271	316.598	321.859
9	-255.524	349.799	1215.726	134.101
10	-749.379	1327.853	713.821	260.179
11	70.744	443.994	-720.508	527.727
12	37.863	352.238	827.667	163.292
13	-148.536	355.911	-643.083	427.750
14	-1148.286	461.839	841.281	273.585
15	-185.804	628.446	-908.161	442.589
16	-761.700	536.850	-3068.089	702.911
17	1321.643	97.571	200.637	221.262
18	1324.286	135.357	59.071	214.946
19	689.374	-3.050	462.117	1.988
20	115.339	258.232	1303.101	63.226

Summary Table for the 30-Block Linear Regression Analysis of Combined Blocks 1 & 2 and Blocks 29 & 30

Subject	Blocks 1 and 2		Blocks 29 and 30	
	Constant	m	Constant	m
1	2858	56.375	-100.411	346.464
2	1047.664	167.201	-106.875	263.625
3	202.637	259.012	1629.951	59.99
4	-935.27	493.706	-64.601	318.524
5	-158.69	417.435	-166.196	336.429
6	641.314	254.456	-477.857	344.643
7	-380.076	376.529	-2553.384	595.634
8	-34.82	346.32	319.607	224.418
9	-631.196	441.554	-1518.559	483.631
10	-137.411	493.339	1421.659	165.741
11	-737.268	439.357	-762.006	393.119
12	1544.284	282.415	227.345	392.47
13	-170.645	391.986	552.615	194.941
14	96.792	259.875	3147.588	-87.426
15	715.738	316.631	1430.345	164.595
16	289.143	278.286	380.702	268.952
17	310.289	280.513	1882.036	56.536
18	247.568	275.247	-58.982	222.268
19	-1892.567	765.485	650.313	91.705
20	421.614	424.307	-1274.554	421.821

Summary Table for the 10-Block Correlation Analysis of Transfer Disruption and Final Block Regression Slope (m)

Correlations

		Difference	m
Disruption	Pearson Correlation	1	.499*
	Sig. (2-tailed)		.025
	N	20	20
m	Pearson Correlation	.499*	1
	Sig. (2-tailed)	.025	
	N	20	20

*. Correlation is significant at the 0.05 level (2-tailed).