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Contextual effects on a well learned task: Isolated or broad?

Matthew J. Parkinson
Edith Cowan University

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Contextual Effects on a Well Learned Task: Isolated or Broad?

Matthew J. Parkinson

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Submitted (October, 2007)

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Abstract

Skill transfer is a fundamental feature in the domain of skill acquisition, however different theories present conflicting ideas regarding prediction of transfer. Anderson's (1982) Adaptive Control of Thought theory posits that the amount of transfer is proportional to the number of shared productions. Logan's (1988) Instance theory in contrast, posits that complete transfer will only occur on tasks which have been experienced before. However, work by Speelman and Kirsner (1997), Speelman, Forbes and Giesen (2004) and Johnson (2005) have produced results that counter the implicit assumptions of these theories. More specifically a disruption from the predicted learning curve was found in situations where both Logan and Anderson would predict complete transfer. Such findings have implications on the theoretical nature of skill acquisition. However these findings involved data that was averaged over many trials, and as such a more specific trial by trial account of the underlying nature of this disruption is not known.

Keywords: Contextual Effects, Adaptive Control of Thought, Instance Theory, Skill Acquisition, Transfer.

Matthew J. Parkinson

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Introduction

It is a widely accepted notion that as an individual practises a given task their performance on the task will improve; that is, the amount of time taken to perform the task or the number of errors made during the task will decrease (Anderson, 1982; Fitts, 1964: Fitts & Posner, 1967; Logan, 1988). This process is usually described as skill acquisition and has featured heavily in recent research (Sohn, Doane & Garrison, 2006; Taatgen & Wallach, 2002; VanLehn, 1996). Of related interest to research on skill acquisition is skill transfer; the degree to which a skill acquired in one situation can assist a task in another situation.

Previous experiments with skill acquisition and transfer have led to a number of theories that try to account for the notion of improved performance as well as skill transfer. The two main theories that seek to explain skill acquisition are Anderson's Adaptive Control of Thought (ACT*) theory and Logan's Instance theory (Anderson, 1982, 1983, 1987, 1993, 1992; Logan, 1988, 1990, 1995, 1998, 2002). While these two theories approach the concept of skill acquisition differently, both theories implicitly suggest that when old skills are carried out in the context of a new task, performance will continue undisrupted. However, work by Speelman and Kirsner (2001) and Speelman, Forbes and Giesen (2004) has produced evidence counter to this assumption.

Although the results of Speelman and his colleagues suggest that performance on a task might be disrupted when individuals encounter a contextual change, the research designs of these studies were such that other possible causes might exist for the disruption. As such Johnson (2005) carried out further research that ruled out these other possibilities. While Johnson's study confirmed that a change in context can disrupt skilled performance, some questions remain as to the nature of this effect.

The current review examines some of the features of this effect to determine its underlying nature.

Skill Acquisition

Skill acquisition, the process by which a novice progresses into an expert, is often described by Fitts and Posner's (1967) sequential stage model. In this model, an individual works through three stages. The first stage is known as the Cognitive stage and describes an individual's new attempts at a given task. In this stage the individual is attempting to identify and develop the crude skills needed to carry out the task. Therefore performance is at its slowest and the number of errors made is at their highest. Attentional resources are also at their peak.

After the initial cognitive stage, practise leads to the associative stage. During this stage, errors in the task are detected and reduced, and appropriate or successful aspects of the task are strengthened, resulting in faster and more accurate ability on the task (Fitts & Posner, 1967).

The last stage is the autonomous stage and it is here that the individual is now so adept at the task that the performance is automatic and unconscious. That is, the task uses minimal attentional resources. In this stage the individual's performance may look effortless; however at such a level, improvement on the task is minimal and may even be asymptotic.

One of the earliest and often cited exemplar of the effects of practise is Crossman's (1959) cigar rolling study. In this study, Crossman measured the speed of production in workers who were making Cuban cigars using special hand operated machines. Crossman found that the worker's performance increased progressively for the first two years, which roughly corresponded to three million trials, before levelling off. While performance levelled off at this point, slight improvements were still being made. It was also noted that this asymptotic point corresponded to the cyclic rate of the machines and thus it was postulated that the levelling of performance might have been due to the limit of the machines rather than the limit of learning. However even if the machine did not have such a limit, performance will still eventually reach asymptotic levels as the human body has physical limits and cannot complete a task in zero seconds.

This description of improvement in performance was subsequently found across a range of differing tasks such as the solving of geometry proofs (Anderson, Greeno, Kline, & Neves, 1981) and reading of inverted text (Kolers, 1975). Given the breadth of tasks and the continual finding of such a pattern of improvement, this pattern has been given the status of a law in Psychology in which there are very few laws (Logan, 1988; Newell & Rosenbloom, 1981). This law is usually known as the power law of learning or the power law of practise because if the performance on a task is plotted as a function of the amount of practise on a task, the amount of improvement decreases according to a power function (see Figure 1).

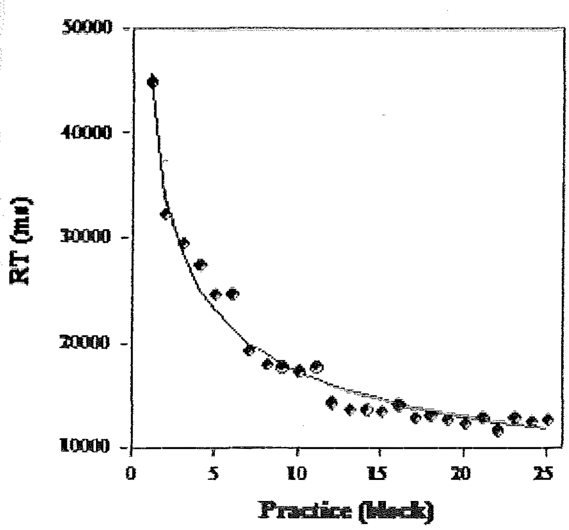


Figure 1. Illustration of skill acquisition data with a power curve fitted (Speelman & Kirsner, 2005).

This power law can be summarised by the equation $T = a + bN^c$. In this equation T represents the amount of time taken to complete the task, a is the asymptote, b is the total amount that can be learned, or put another way, the difference between the time on the first trial and the asymptote, N is the amount of practise, and c is the learning rate. This learning rate falls between zero and negative one, with values closer to negative one indicating a rapid rate of learning.

While power functions have been shown to fit the data well, there has been some question over their universal application, as the majority of evidence regarding the power law has been attained using averaged data (Heathcote, Brown, & Mewhort, 2000). Moreover there is evidence that when individual data are plotted as opposed to averaged data, an exponential function provides a much better fit than does a power function (Heathcote et al., 2000). While it has been suggested that exponential functions best approximate what is happening during learning, Heathcote et al. accept that power functions may be useful for revealing general trends about the nature of skill acquisition.

Anderson's ACT Theory*

Currently, one of the dominant theories of skill acquisition is Anderson's (1982, 1983, 1987, 1993, 1992) Adaptive Control of Thought (ACT*) theory. According to Anderson, behaviour is governed through the use of production rules. Production rules are condition-action or if-then statements that provide information on how to respond to a given situation. An example of a simple production rule would be:

IF the goal is to form the present participle of a verb

THEN add '-ing' to the verb

A production rule has two parts, the IF component being a particular goal or task that the individual has, and the THEN component essentially being the memory that the individual has and utilises in the attainment of their goal. While the goal in the example can be considered simple as only one production rule would be needed to attain it, Anderson notes that more complex goals may need the use of several production rules to reach the goal.

Like Fitts and Posner's (1967) model, in Anderson's theory people move through three stages as they progress from a novice to a skilled person on a particular task. The first stage is the declarative stage and it corresponds to Fitts and Posner's cognitive stage. This stage represents an individual's beginnings with a task whereby the individual encodes knowledge in a declarative form from explicit facts or instructions regarding the task, or by using a problem solving strategy such as analogy from prior experience.

The second stage is the knowledge compilation stage and corresponds with Fitts and Posner's associative stage. During this stage knowledge in the declarative form is compiled into a procedural form through the use of productions. It is throughout this stage that a task can be undertaken with less reliance on interpretive procedures (Anderson, 1982).

Finally there is the procedural stage which corresponds to Fitts and Posner's autonomous stage. During this stage the individual is considered proficient at the skill and performance becomes more automatic with less demand on attentional resources.

While the three stages of skill acquisition in ACT are similar to those described by Fitts and Posner, Anderson expands on the earlier account by suggesting three ways that explain how practise improves task performance; namely rule composition, strengthening and proceduralisation.

When an individual first practises a task they will use explicit instructions or other crude ways of approximating the task, but with further practise they will develop productions. This process of proceduralisation involves slower declarative information being transformed into faster and more efficient procedural information (productions). Improvement in performance is partly attributed to this process as an individual can use more specific productions from long term memory, rather then having to hold onto large amounts of declarative information in working memory, resulting in less conscious cognitive effort and faster reaction times.

A particular task may require a number of productions before the goal is reached, however with enough practise the individual can collapse some of these productions together, reducing the number of productions needed to reach the goal, and thus create a more efficient and quicker strategy.

An example of the composition process is provided below. This example comes from Speelman and Mayberry (1998), and is designed to illustrate the development of an algebra skill.

(P1)	IF	goal is to solve for x in equation of the form a = bx + c
	THEN	set as subgoal to isolate x on RHS of equation.
(P2)	IF	goal is to isolate x on RHS of equation
	THEN	set as subgoal to eliminate c from RHS of equation.
(P3)	IF	goal is to eliminate c from RHS of equation
	THEN	add –c to both sides of the equation.
(P4)	IF	goal is to solve for x in the equation and it has been isolated on the RHS of the equation
	THEN	LHS of equation is solution for x.

If an individual practises many equations of the form a = bx + c, then composition will result, with productions 2 and 3 being collapsed into:

If goal is to isolate x on RHS of the equation

THEN add –c to both sides of the equation.

If practise is continued, productions 1, 4 and 5 would be collapsed to produce the more efficient production rule:

IF goal is to solve x in the equation a = x +c

THEN subtract c from a to form the solution.

Consequently, the original goal is now accomplished in one step as opposed to the original five, reducing the workload and resulting in faster reaction times for the task.

Lastly performance is enhanced due to strengthening, as, according to Anderson, every time a declarative fact or production rule is applied it becomes stronger. Strength in the ACT theory pertains to the probability that a given production rule or declarative fact will be utilised. Anderson also designated numerical values to indicate the strength of a particular production. Using ACT a new production has a starting value of 0.1 and has an additive value of 0.025 each time it is successfully employed. However if the production is applied unsuccessfully, its value is reduced multiplicatively by 0.25, meaning the application of incorrect productions has a stronger effect then correctly applied productions. Thus while these numbers are somewhat arbitrarily chosen by Anderson, they do provide an explanation of how errors in performance are reduced (Anderson, 1982).

Logan's Instance Theory

A second fundamental theory of skill acquisition is Logan's (1988, 1990, 1995, 1998, 2002) instance theory. The core tenet in this theory is that individuals become better at tasks, not because of various qualitative changes, as is posited in Anderson's theory, but due to an increase in memory traces known as instances.

In this theory, there are three underlying assumptions. The first assumption is that encoding of a memory trace is an obligatory and unavoidable consequence of attending to a stimulus. However this does not mean that it will necessarily be retrieved, only that the encoding will be obligatory. Logan's second assumption states that what information is available regarding a given stimulus will be retrieved from memory as an unavoidable consequence of attention. Lastly the theory assumes that every encounter with a stimulus is encoded, stored and retrieved separately.

According to this theory, when an individual is first presented with a novel task, they will try and complete the task using a general algorithm. For example a child who is asked to add 8 and 2 may use their fingers or crude knowledge of counting to work out the answer. Once the task has been completed, an 'instance', which comprises of both the solution and the task, is encoded into memory. According to Logan, the next time the same task is encountered, the individual will again begin to solve the problem using the general algorithm, while simultaneously retrieving an instance. The response that produces the solution the fastest is used. With additional exposure to the same task, the number of instances available increases while the speed of the algorithm remains at a constant. The more instances there are, the more likely one of them will be faster then the algorithm and therefore the more likely an instance will be executed over the algorithm.

It is through this metaphorical 'race' between the algorithm and instances that Logan is able to explain the speed-up of performance that is associated with practise; whereby an individual gradually shifts from using the general algorithm to using instances accessed directly from memory. Indeed Logan views automaticity as performance on a task in which the individual no longer has to use the algorithm, but instead relies entirely on instances.

Skill Transfer

Given the underlying explanations of how skills are acquired, both Logan and Anderson make quite specific predictions on the transfer of these skills. Skill transfer refers to the amount to which a skill that is acquired in one setting aids in the execution or acquisition of a skill in a different situation (Greig & Speelman, 1999). To examine transfer researchers typically present people with a number of trials on a given task called the training phase, and plot their performance graphically. They will then give the same group of people another task, usually referred to as the transfer phase, and again plot their performance. The transfer phase can then be compared to the training phase or to a different group of people who did not do the original training phase to examine if transfer occurred.

Generally speaking there are three types of transfer; positive, partial and zero transfer. Complete transfer is said to have occurred if performance in the transfer phase, once plotted, continues in line with what would be predicted from the power function that describes the training learning curve. Essentially this means that performance on the new task is identical or near identical with performance on the last part of the training phase. Partial transfer is seen when transfer performance is better then initial performance on the training phase, but is not as advanced as performance at the end of training. This means that the training phase has helped the individual in performing the new task, but not to the point where they can carry out the new task as efficiently as the training task. Lastly there is zero transfer, which occurs when performance on the transfer phase is similar to what is seen at the initial part of the training stage. Essentially this means that the individual has experienced no gain in performance from being exposed to the prior task.

While it is these three types of transfer that are generally seen when examining the notion of transfer, a study by Luchins (1942) suggests that negative transfer is possible. Negative transfer is said to have occurred when performance on a task is hindered through exposure from a previous task. The most well known example of this is known as the Einstellung effect in which participants were given a number of water jug problems to solve. Luchins found that participants would continue to solve the problems using the same successful strategy, even when a simpler and more efficient solution could be used. While this phenomenon is generally labelled as negative transfer, Anderson (1987) suggested this may be an example of positive transfer of a less efficient skill.

Both Anderson's ACT and Logan's instance theory make quite specific yet different predictions about the workings of transfer. The key difference between the two theories centres on how specific or how general they can be. According to Anderson, the amount of transfer that occurs can be accounted for by the number of shared productions two tasks share. If two tasks share a significant number of productions then partial transfer is likely and complete transfer is possible. According to Anderson even if two tasks share a small number of productions, partial transfer is still likely. In this way ACT is flexible and can account for the whole range of transfer outcomes, from zero to complete transfer of two tasks.

This was highlighted in a study by Speelman and Kirsner (1997) who examined the role of transfer using syllogistic reasoning on 128 university students. For this task, participants were to answer either true or false to universal affirmative syllogisms such as:

All of the Artists are Beekeepers
All of the Beekeepers are Chemists
Therefore
All of the Artists are Chemists

For the training phase participants were presented with 288 such syllogisms, whereby the first two premises were presented on a computer screen, and once the participant had pressed 'ready', they would disappear and a conclusion would then be presented. The participant was then to answer true or false to the given conclusion.

While all of the syllogisms were of the same structure and could be solved using the same type of strategy, none of the syllogisms were repeated. Thus in terms of transfer prediction, Anderson's ACT and Logan's instance theory make quite different predictions. For Logan, as no syllogism was repeated, there should be no transfer as there are no prior instances to employ. As the instance theory asserts that the algorithm does not improve performance, reaction times and the number of errors should be similar in both the training and transfer conditions (Speelman & Kirsner, 1997).

However according to the ACT theory, there is likely to be transfer as while no syllogisms were repeated, they all shared a similar form and thus it was highly likely that all syllogisms were solved with common productions. As such these underlying productions will be refined and strengthened leading to an increase in performance. Indeed the results revealed that both complete and partial transfer was shown, supporting ACT while revealing a fundamental problem with instance theory.

While in this study many similarities existed between the two tasks, according to ACT, it is not their similarity so much, but their shared productions which is central in the role of transfer. This was highlighted by Singley and Anderson (1989) who showed that zero transfer can occur between tasks that are superficially quite similar. Essentially this means that while two tasks may seem to appear quite similar, transfer may be small as they may not share productions. However this abstract notion of productions has been a criticism of the ACT theory as it makes the theory virtually impossible to falsify (Carlson & Schneider, 1989). Indeed Anderson (1987) himself was aware that being able to predict the amount of transfer is not an easy task as individuals can not verbalise any underlying productions while engaging in a task.

While Anderson's ACT theory is quite broad with its account of transfer, in contrast Logan's instance theory is more restrictive. According to Logan, an instance is highly specific to the experiences encountered. As a result no transfer will occur unless the transfer task is identical to the training task. This is because in this theory the individual has no stored information or 'instances' on a task that is different, and consequently their performance will be as error prone and as slow on the task as if they had never been exposed to the training task. However should the transfer task be identical in nature to the training task, then complete transfer should occur whereby the individual's performance should be the same or slightly better than their previous exposure. Therefore Logan posits a dichotomous view of transfer where partial transfer can not occur, only complete or zero transfer is possible.

The role of transfer in the instance theory can be highlighted through a study by Logan and Klapp (1991) that was conducted to examine the role of extended practise on automaticity. For this study Logan and Klapp presented individuals with a number of alphabet-arithmetic equations such as A + 2 = C, to which the participants were to answer if the equation was true or false. To answer such a task, participants were to count forward or backwards a given number of spaces in the alphabet (i.e., 2) from the letter given (i.e., A). To examine the effects of transfer in this experiment Logan and Klapp gave the participants equations that used one half of the alphabet for the training phase, and then employed the other half of the alphabet for the transfer phase.

The results revealed that, as predicted by the instance theory, the more trials the participants were exposed to, the faster they were at answering the equations. According to Logan and Klapp, this is because the participants almost certainly would have needed to use a general algorithm when first presented with such novel questions, but as more instances were created with increased exposure, the participants were relying more on memory to produce their answer, rather then having to go through the laborious task of manually working out the correct response. Indeed when they asked participants how they arrived at their answers for the first session, over 90% reported that they used counting. More importantly, when the participants were presented with the other half of the alphabet that they had not yet been exposed to, reaction times increased significantly and performance times returned to levels similar to the initial sessions of the training phase. Also, participants revealed that they went back to counting 85% of the time, results that according to Logan show that transfer is item specific.

Further support for item specific transfer came from Lassaline and Logan (1993) who conducted a spatial-numerosity task. For this experiment Lassaline and Logan presented participants with 6 – 11 elements on a computer screen and asked them to count the number of elements as quickly as possible while also being as accurate as possible. Throughout the initial sessions reaction times increased in a linear fashion as the number of elements increased, suggesting that participants were using the general algorithm of counting to generate a response. However as the particular stimuli were repeated, and so the number of practise sessions increased, the participant's reaction times to the different number of elements was becoming more homogenous, suggesting that there was a shift from the general algorithm of counting, to memory recall (i.e., participants recognised the stimuli and remembered their answer). Furthermore when the participants were presented with the transfer task, which was the same task but with different patterns, reaction times were found to increase with numerosity and performance times in general were comparable to the training phase, highlighting the item specific nature of transfer as described by the instance theory.

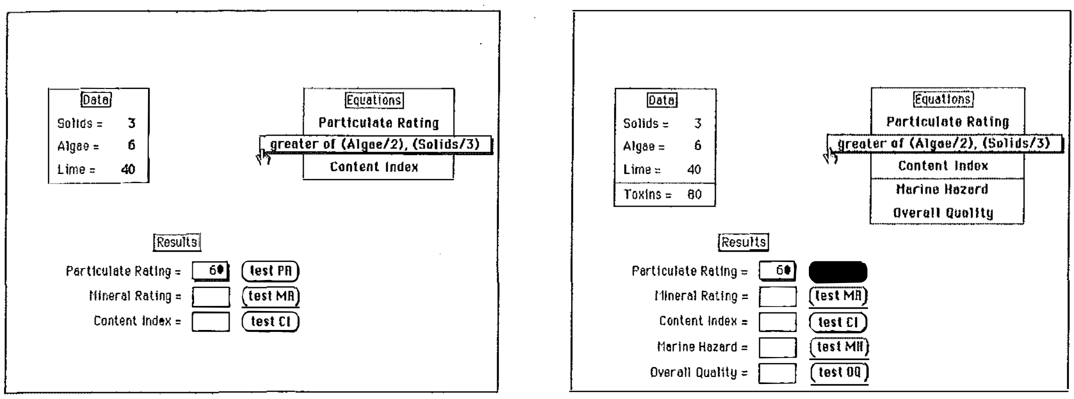
Counter Research

While Speelman and Kirsner's (1997) research supports the ACT theory, other research results are counter to both Anderson's and Logan's. Speelman and Kirsner (2001) examined whether performance during a transfer task could be predicted on the basis of performance from a training task. To investigate this, they gave participants a fictional water analysis problem which could be solved by simple arithmetic. The training phase of this task involved three components, while the transfer phase used the exact same initial three components plus two new components of a similar nature. The participants were randomly divided into two groups and only the experimental group experienced the two novel components while the control group were presented with the same components for both the training and transfer phases. Each component was separate and the layout was such that each component was to be solved sequentially.

Speelman and Kirsner's (2001) experiment was designed to test a fundamental and implicit notion of both ACT and instance theory, which is that performance of old skills will continue in line with the power law of learning, even when contextual features are changed. As the experiment was only measuring performance on the three components in the transfer phase, the additional two components should have no bearing on performance. Indeed according to Anderson's ACT, as the exact same components were being used and measured, the productions and processes employed would be the same resulting in complete transfer. Similarly Logan's instance theory would predict complete transfer as participants would be able to employ instances that were created during the training task to solve the problems on the transfer task.

However, the results revealed that when the experimental group began the transfer phase, their performance on the initial three components was slowed and disrupted, rather then following the predicted path of the power law. Even though the three components in both the training and transfer phase were identical, the results suggest that when the context is altered (in this case by two additional novel components) this can affect an individual's performance. While it should be noted that only performance times were disrupted, and not accuracy, the evidence of partial transfer instead of complete transfer is counter to what ACT and instance theory would predict.

While Speelman and Kirsner's (2001) research suggests that the context of a task may affect predictions using the power curve, other possibilities needed to be considered. One possible reason for the disruption in transfer could stem from the visual differences between the training and transfer phase (Forbes, 2000; Speelman, Forbes & Giesen, 2004). Given that the training phase used three components and the transfer phase used five, the visual appearance of these two conditions is considerably different. This can be highlighted in Figure 2, where there are a greater number of components in each section of *Data*, *Equations* and *Results.* This means that there is more information for the participants to process, and perhaps leading the participants to think that the transfer task had now become more complex, even though the initial three components stayed the same for both training and transfer (Speelman, Forbes & Giesen, 2004). At a bare minimum, the participants might have thought it was necessary to check whether the new information required examining before continuing (Forbes, 2000).



Version one Version two

Figure 2. A comparison of Speelman and Kirsner's (2001) three and five component task.

Since visual complexity might have been a confounding factor in the results produced by Speelman and Kirsner (2001), Speelman, Forbes and Giesen (2004) designed an experiment whereby the items in both the training and transfer phases were visually the same in appearance. To achieve this, participants were given simple multiplication problems from the six times table for the training phase such as 6x3 = _. These same multiplication problems were also used for the transfer task, however randomly interspersed with these problems were distractor problems that were of a similar nature to the target questions but differed slightly in form; for example 6x_ = 18.

More importantly, only one question at a time was presented on the screen and each question was presented separately from each other. This meant that the visual appearance of both the training and the transfer phases were the same, controlling for the possible confounding variable that was present in Speelman and Kirsner's (2001) study. As only the multiplication problems were being measured in the transfer phase, if a disruption in performance was found during this phase then it suggests that contextual change, rather then visual complexity is possibly the cause of the transfer disruption.

The results revealed that there was a disruption in performance on target problems at the beginning of the transfer phase, similar to what was found in Speelman and Kirsner's (2001) study. Given that visual differences have been ruled out, Speelman et al. (2000) concluded that the disruption was caused by this contextual change. Thus these findings challenge the implicit assumption in both Anderson and Logan's theories that performance of old tasks will continue to improve according to the power curve.

However while this experiment does eliminate the possibility of visual complexity, it is possible that another interpretation apart from contextual differences could result from such a design. Given that the transfer phase of the experiment used the exact same problems as the training phase as well as additional distractor tasks, the items in the transfer phase are now spaced further apart than those in the training phase. As such it is also possible that the participant's disruption in performance times is a reflection of memory decay, rather then an effect of contextual changes. That is, during transfer, when a distractor problem is presented, because it is relatively unfamiliar compared with the target problems, participants could take longer to solve them. As a result, some time passes before the next target problem is presented, which could result in some form of decay in whatever memory representation that is responsible for skilled performance (i.e., productions or instances); leading to a slower performance time on the next target problem.

While the results of a contextual change impacting performance would be contradictory to both Anderson's and Logan's theories, the findings by Speelman and

Kirsner (2001) and Speelman, Forbes and Giesen (2004) are such that other interpretations of the data are possible. This led to an experiment by Johnson (2005) in which both the visual differences and the issue of spacing were addressed. Johnson's design used the same multiplication problems from the six times table as used by Speelman, Forbes and Giesen (2004) for both the training and transfer task. However in Johnson's study, every trial in both the training and transfer phases consisted of two components; namely a target problem and a distractor problem.

As such the participant would first be presented with a multiplication problem of the form 6 x 3 =_, to which they were instructed to press the space bar once they had thought of the answer. Two potential answers were then presented and the participant was required to select the correct answer. After this, they would be asked to add or subtract a given number from the correct answer. A trial in this experiment, then, was a multiplication problem and an addition/subtraction problem. Both the training and transfer phases of this experiment consisted of 12 blocks of 6 trials each.

The exact same multiplication problems were used in both the training and transfer phases, with half of the participants receiving addition distractor questions for the training phase, with subtraction distractor questions for the transfer phase, and vice versa for the other participants for counterbalancing. With this design, the problems of visual differences and unequal spacing is avoided as both the training and transfer phases have the same number of items in them, and each problem is presented one at a time.

The results of this study confirmed what Speelman and Kirsner (2001) and Speelman Forbes and Giesen (2004) found with their studies, as Johnson (2005) found that the first block of transfer was significantly slower then the last block of the training phase (See figure 3).

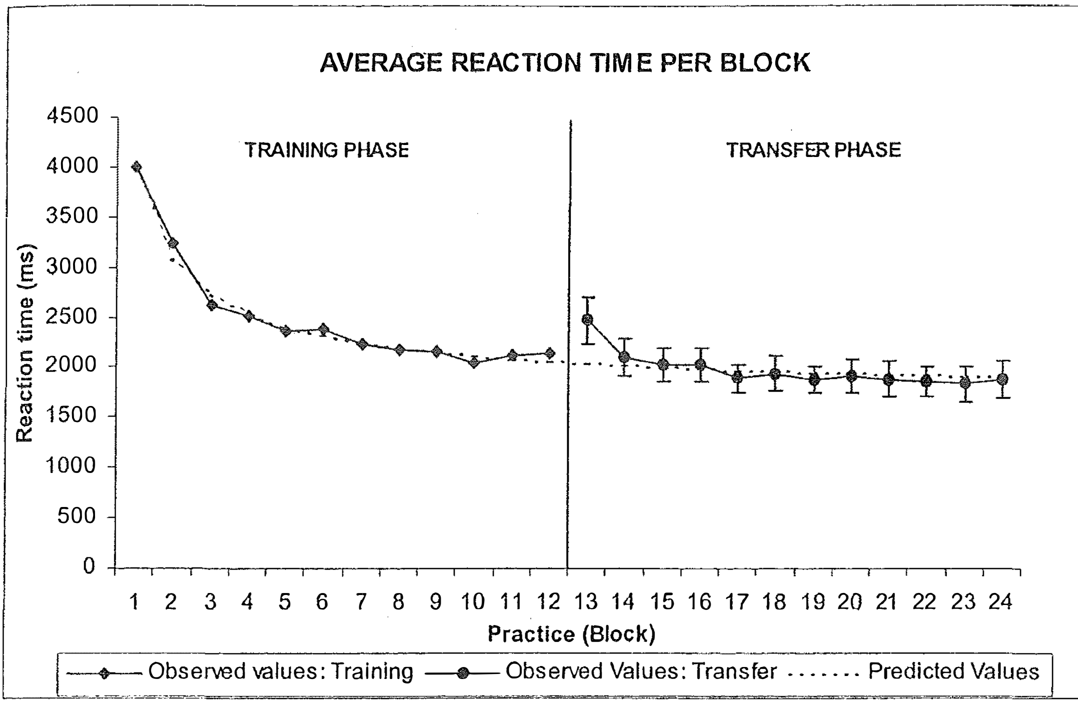


Figure 3. The disruption of transfer performance from predicated values as reported by Johnson (2005).

While Johnson's study solidifies the notion that contextual changes can disrupt performance, it is not known how this effect is distributed on a trial by trial basis within the disrupted block. Such research would help to elucidate the nature of the disruption as well as the effect contextual changes have on a learnt task. The results may also be informative with regard to how the theories of Anderson and Logan could be modified to cope with the disruption associated with context change.

One possibility is that the effect of the disruption is isolated to the first multiplication trial after the contextual change, with performance regaining its predicted path by the next trial. While this would still be an issue for both the ACT and instance theories, it could be explained by Logan and Anderson perhaps as an isolated 'surprise' effect, whereby the participant is momentarily distracted by such a change before regaining mental clarity on the task. A second possibility is that the disruption is not isolated, but is spread out more broadly across the trials, with performance slowly regaining the predicted path. This possibility would present a greater challenge to both the ACT and instance theories, as it suggests a more systematic disruption rather then a surprise effect.

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Contextual Effects on a Well Learned Task: Isolated or Broad?

Matthew J. Parkinson

Abstract

The present study examined the role of skill acquisition and skill transfer in relation to both Anderson's (1982) Adaptive Control of Thought theory and Logan's (1988) instance theory. The study involved 59 participants being presented with multiplication problems from the six times table, followed by a distractor task in the form of an addition or subtraction question. The training phase consisted of 12 blocks of trials, with six trials per block. The multiplication problems remained constant in both the training and transfer phases, while participants receiving addition problems in training then received subtraction questions in transfer and vice versa. Only reaction times for the multiplication problems were analysed and the results showed that there was a significant disruption when the participants encountered the transfer phase. Further analysis on a trial by trial basis indicated that in the three trials following the contextual change, performance was significantly slower than the first trial of the transfer phase, discounting a fleeting 'surprise' effect. A power function fitted to the reaction times of the transfer trials following the context change supported the gradual return of performance to pre-transfer levels. The results contradicted both Anderson's and Logan's predictions, and suggest that with practise, a mental set is developed which can then be disrupted through contextual change.

Keywords: Contextual Effects, Adaptive Control of Thought, Instance Theory, Skill Acquisition, Transfer.

Matthew J. Parkinson

Associate Prof. Craig Speelman

29th of October, 2007

Introduction

The process through which an individual acquires new skills and becomes more efficient at those skills with practise is known as skill acquisition (Anderson, 1982; Fitts & Posner, 1967; Logan, 1988). Closely related to this is skill transfer, which refers to the degree to which a skill that is learned in one situation, can aid in the acquisition or performance of a task in a different situation.

Previous research on both skill acquisition and skill transfer has resulted in a number of theories that seek to explain and conceptualise the understandings of improved performance and skill transfer. The two most prominent theories of skill acquisition and transfer are Anderson's ACT theory (Anderson, 1982, 1983, 1987, 1992, 1993) and Logan's instance theory (Logan, 1988, 1990, 1995, 1998, 2002). While both theories differ in their theoretical approach to skill acquisition, they both share the implicit assumption that performance will continue to improve smoothly with practise, even when executed in the context of a new task. However research by Speelman and Kirsner (2001) and Speelman, Forbes and Giesen (2004) produced results that question this implicit assumption.

While Speelman and his colleagues presented evidence which suggested performance on a task may be disrupted when an individual encounters contextual change, the designs of these studies made it possible for other interpretations of what may be causing the disruption in performance. This led to a study by Johnson (2005) that ruled out other such interpretations.

However, while Johnson's study confirmed that a change in context can disrupt skilled performance, some questions remain as to the nature of this effect. Thus the current study was designed to examine some of the features of this effect to determine its underlying nature

Skill Acquisition

The process of skill acquisition, through which a beginner progresses into a skilled expert, is often described by Fitts and Posner's (1967) sequential stage model. In this model, an individual progress through three stages. The first stage is known as the cognitive stage and describes an individual's new attempts at a given task. In this stage the individual is attempting to identify and develop the crude skills needed to carry out the task. Therefore performance is at its slowest and the number of errors made is at their highest. Attentional resources are also at their peak.

After the initial cognitive stage, further practise leads to the associative stage. During this stage, errors in the task are detected and reduced, and appropriate or successful aspects of the task are strengthened, resulting in faster and more accurate performance on the task (Fitts & Posner, 1967). Lastly, with further practise the individual progresses into the autonomous stage. At this stage the individual's skill level is at its highest, and performance on the task is considered automatic. While their performance is at a high level, improvement beyond this point is minimal.

The effect of practise on performance is highlighted by an early and now classic study on skill acquisition conducted by Crossman (1959). In this study, Crossman measured the speed of production of workers who were making Cuban cigars using special hand operated machines. Crossman found that the worker's performance increased progressively for the first two years, which roughly corresponded to three million trials, before levelling off. While performance levelled off at this point, small improvements were still being made. An asymptotic point in the learning curve was also observed, and this corresponded to the cyclic rate of the machines and thus it was postulated that the levelling of performance might have been due to the limit of the machines rather than the limit of learning. However even if the machine did not have such a limit, performance would still eventually reach asymptotic levels as the human body has physical limits and cannot complete a task in zero seconds.

This progression of improvement was not only found on the cigar making task. Other studies have reported this pattern across a range of diverse tasks such as the reading of inverted text (Kolers, 1975) and the solving of geometry proofs (Anderson, Greeno, Kline, & Neves, 1981). As this pattern of improvement was continually found across a large range of tasks, it was granted the status of a law in Psychology in a discipline where only a small number of laws exist (Logan, 1988; Newell & Rosenbloom, 1981). This law is named the power law of learning or the power law of practise because when performance is plotted as a function of practise on a task, improvement decreases in line with a power function. This is highlighted in Figure 1.

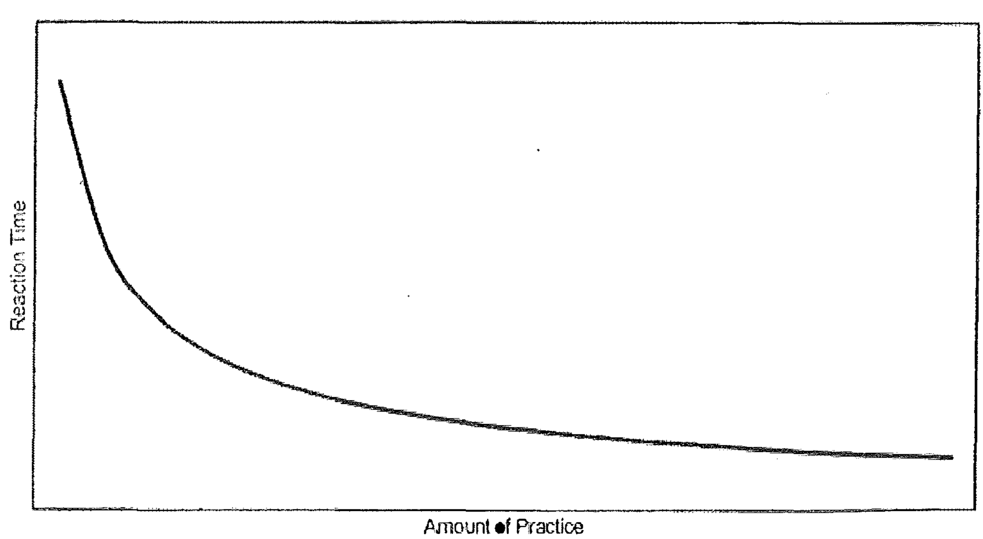


Figure 1. Representation of the power law of learning.

The power law can be summarised by the equation $T = a + bN^c$. In this equation T represents the amount of time taken to complete the task, a is the asymptote, b is the total amount that can be learned, or put another way, the difference between the time on the first trial and the asymptote, N is the amount of practise, and c is the learning rate. This learning rate typically falls between zero and negative one, with values closer to negative one indicating a rapid rate of learning.

It should be noted that learning curves typically display asymptotes only when practise on a task has extended over very long periods. When practise extends over a short period, power functions with asymptotes equal to zero (i.e, $T = bN^C$) provide a good fit to the learning curve (Anderson, 1982).

Anderson's ACT Theory*

The most prominent theory on skill acquisition is Anderson's (1982, 1983, 1987, 1992, 1993) Adaptive Control of Thought (ACT*) theory. According to Anderson, behaviour is governed through the use of production rules. These production rules are condition-action or if-then statements that provide information on how to respond to a given situation. An example of a simple production rule would be:

IF the goal is to form the past tense of a verb

THEN add 'ed' to the verb

Production rules have two parts, the first being the IF component which is a particular goal that the individual has, and the second is the THEN component which is essentially the memory that the individual has and uses in the attainment of their goal. While the goal in the example is simple in nature as only one production rule was needed to attain it, Anderson notes that more complex goals may need the use of several production rules to attain the goal.

As in Fitts and Posner's (1967) model, Anderson proposes that people move through three stages as they progress from a novice to an expert on a particular task. The first stage is the declarative stage and it is here that the individual encodes knowledge in a declarative form from explicit facts or through the use of problem solving strategies such as analogies from prior experience. The second stage known as the knowledge compilation stage involves knowledge in declarative form being compiled into a procedural form through the use of productions. In this stage tasks can be undertaken with less dependence on interpretive procedures (Anderson, 1982). Lastly there is the procedural stage where proficiency on the task is at its highest and performance can be executed with the use of minimal attentional resources.

While Anderson's model is similar to the three stage model posited by Fitts and Posner, Anderson expands their work by suggesting three ways in which practise improves performance on a task; namely proceduralisation, rule composition, strengthening.

When an individual first practises a task, explicit instructions or other crude ways of approximating the task will be employed. However through a process known as proceduralisation, the slow process of applying declarative information is transformed into a faster and more efficient process of applying procedural information (productions). As a result of this process, an individual can use more specific productions from long term memory, rather than having to hold onto large amounts of declarative information in working memory, resulting in less conscious cognitive effort and faster reaction times.

Certain tasks may also require the execution of a number of productions before the goal is attained. However with enough practise some of the productions can be collapsed, known as rule composition, which results in a reduced number of productions being needed to reach the goal, and thus creating a more efficient and faster strategy.

Performance is also improved due to strengthening. According to Anderson, every time a declarative fact or production rule is applied it becomes stronger. Under the ACT* theory, strength denotes the probability that a given production rule or declarative fact will be employed. When a production is utilised successfully, it gains strength additively, however when unsuccessfully applied its strength is reduced multiplicatively. In this way the application of incorrect productions has a stronger effect then correctly applied productions, and this provides an explanation of how errors in performance are reduced (Anderson, 1982).

Logan's Instance Theory

Another central theory of skill acquisition is Logan's (1988, 1990, 1995, 1998, 2002) instance theory. This theory states that performance improves because of increases in memory traces known as instances. In this way, Logan is positing a more quantitative approach to skill improvement, as opposed to Anderson's theory which states that improvement in a skill is due to more qualitative aspects.

This theory rests on three underlying assumptions; namely that (1) encoding of a memory trace is an obligatory and unavoidable consequence of attending to a stimulus (2) what information is available regarding a given stimulus will be retrieved from memory as an unavoidable consequence of attention (3) that every encounter with a stimulus is encoded, stored and retrieved separately.

According to the instance theory, when an individual first encounters a new task, they attempt to complete the task through the use of crude knowledge and strategies known in this theory as a general algorithm. Once the required goal has been met, an 'instance', which comprises both the task problem and the solution, are stored in memory. The next time the person is exposed to the same task, they will again attempt to solve the problem using the genal algorithm, while simultaneously retrieving an instance (i.e., they will try to remember what they did the last time). Whichever response produces the solution the fastest is employed.

With further exposure to the same task, the number of instances available increases while the speed of the algorithm remains at a constant. As the number of instances increases, it is more likely one of them will be retrieved faster than the execution of the algorithm, and therefore it is more likely an instance will be employed over the algorithm. It is through this metaphorical 'race' between the algorithm and instances that Logan is able to explain the speed-up of performance that is associated with practise.

Skill Transfer

Both Logan and Anderson's theories give specific predictions regarding the transfer of such skills. Skill transfer refers to the amount to which a skill that is acquired in one setting will aid in the execution or acquisition of a skill in a different situation (Greig & Speelman, 1999).

To examine transfer, researchers typically present people with a number of trials on a training task, and plot their performance graphically. They will then present another task known as the transfer phase to the same group of people, and again plot their performance. The transfer phase can then be compared to performance in the training phase, or to a different group of people who did not do the original training phase to examine if transfer occurred.

Generally speaking three types of transfer exist; complete, partial and zero transfer. When plotted, if performance in the transfer phase continues in line with what would be predicted from the power function that describes the training learning curve, complete transfer is said to have occurred. Partial transfer occurs when transfer performance is better than performance at the beginning of training, but not as fast as is seen at the end of the training phase. This suggests that the training task has aided the learning of the transfer task to some extent.

Finally, zero transfer is said to have occurred when transfer performance resembles that of training performance. That is, initial transfer performance is as slow as initial training performance. Thus, no gain has been made from being exposed to the training task. While these three types of transfer comprise the most often reported forms of transfer, negative transfer has been reported, whereby the training task has a negative effect on the performance of the transfer task (Luchins, 1942). However it is possible this might be positive transfer of a less proficient skill (Anderson, 1987).

The ACT* and instance theories make quite different, yet specific predictions regarding the nature of transfer. In particular, the two theories differ in how broadly they can account for transfer. According to ACT* theory, as transfer is governed by the number of shared productions, the more productions two tasks have in common, the greater the transfer will be. According to Anderson, even if two tasks share only a small number of productions, partial transfer is likely. This is in contrast to Logan's Instance theory, whereby no transfer will occur unless the training task and transfer task are identical. This is because, according to instance theory, if no 'instances' are stored the individual has no stored information to use on the transfer task, and their performance will be as slow and inaccurate as it would be had they never been exposed to the training task. In this way, the instance theory has a more narrow view of transfer, where ACT* is able to account for a greater range of transfer outcomes.

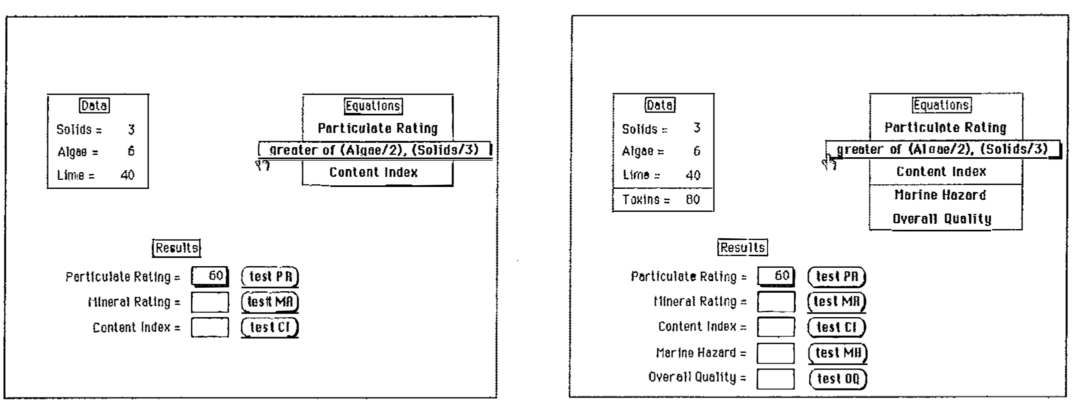
Counter Research

A study conducted by Speelman and Kirsner (2001) examined whether performance on a transfer task can be predicted from the performance on a training task. To examine this they developed a fictional water analysis task in which various water quality questions could be solved by participants on a computer using simple arithmetic. The experiment consisted of a training phase and a transfer phase. The training phase involved solving three independent problems, while the transfer phase consisted of the same three problems plus the addition of two new problems. The participants were randomly divided into two groups and only the experimental group were given the two novel components, while the control group were presented with the same components for both the training and transfer phases.

In this way, Speelman and Kirsner could examine an implicit assumption contained in both the ACT* theory and Instance theory, in which the performance of a well learned skill will continue to follow the power law of learning when in the context of a new task. Given that the experiment was only examining the performance speed with the three components in the transfer task, and excluded the two additional components, performance times should continue in line with the power function that described the training learning curve. Anderson's ACT theory would predict complete transfer, given that both the training and transfer tasks share identical productions. Logan's instance theory would also predict complete transfer, as the participants can utilise the instances which were developed in the training task with the transfer task.

However, the results indicated that when the experimental group continued into the transfer phase, their performance was disrupted and deviated from the predicted path of the power function. Thus, although the training and transfer tasks were being measured on the three identical task components, the results suggest that context change can affect performance on an old skill. This is in direct contrast to both the ACT and instance theory, both of which would predict complete transfer and a continuation of the learning curve without disruption.

While these results suggest that contextual change is responsible for creating a disruption in a well learned task, other interpretations of the data are possible. One possibility for the disruption posited by Speelman, Forbes and Giesen (2004) relates to the differences in visual complexity between the two phases. As can be seen in Figure 2, when an individual encountered the training phase, they are presented with additional components.



Training Task Transfer Task

Figure 2. A screenshot of the three and five component task used in Speelman and Kirsner's (2001) experiment.

The differences in the visual appearance between the two versions of the task may represent a possible confound. In the transfer version of the task the participants now have more information to process, and this may lead them to believe that the transfer task is more complex then the training task, delaying their reactions.

To rule out visual complexity as a confounding factor, Speelman, Forbes and Giesen (2004) created an experiment where both the training and transfer phases where visually identical. To do this, participants were asked to solve simple multiplication problems which were taken from the six times table such as 6x2 = _. The transfer phase then consisted of those identical questions, with additional distractor problems of the form 6x_ = 12, randomly dispersed throughout. The questions were presented one at a time both in the training phase and the transfer phase, creating identical visual appearances and controlling for the possible confounding factor of visual complexity. Given that visual differences have been controlled for, and that only the multiplication problems were being analysed for both the training and transfer phases, if a disruption is present then it would suggest contextual change may be the cause of such a disruption.

When the Speelman et al. (2004) results were analysed a disruption was present. Therefore, with visual differences controlled for, contextual change appears to be sufficient to cause disruption. However another possible explanation for the result exists that could account for the data which centred around memory decay. While the transfer phase used the same items as were used during the training phase, the transfer phase also included a number of distractor items. As a result, the problems that the participants were exposed to during the training task are now presented with a greater average time in between repetitions. It could be argued that a reduction in performance on these items could be a result of memory decay, rather then a contextual effect.

This led to an experimental design by Johnson (2005) which controlled for both the issue of visual complexity as well as memory decay. Johnson's experiment was similar in nature to what was used in Speelman, Forbes and Giesen's (2004) experiment, in which participants were asked problems from the six times table. However in this design, participants were presented with a multiplication problem, which was then followed by a distractor problem in both the training and transfer phases. That is, when a participant began the task, a multiplication problem such as 6x8 =_ would appear on the screen, to which they were to press the spacebar once they have worked out their answer. Two possible answers, one correct and one incorrect would appear in the bottom corners, and the participant was to the select their answer. Following this, the participants were instructed to either add or subtract a given number from the correct answer. This was the distractor task, and again once the participant had thought of their answer, they were to press the space bar and then choose from two possible answers.

A combination of a multiplication problem and an addition/subtraction problem were together known as a trial, and six such trials were analysed as a block. Both the training phase and transfer phase consisted of 12 blocks, with half the participants being presented with addition problems in the training phase and the other half receiving subtraction problems. For the transfer phase, the distractor task was swapped, so those that received addition problems now received subtraction problems and vice versa.

As the same multiplication problems were presented in both the training and transfer phases, as well as both phases being composed of the same number of items, the issues of visual complexity and memory decay were controlled for in Johnson's (2005) study. The results of the study however, still supported the findings of Speelman and Kirsner (2001) and Speelman Forbes and Giesen (2004). That is, there was a disruption in performance times when the participants encountered the context change (Figure 3)

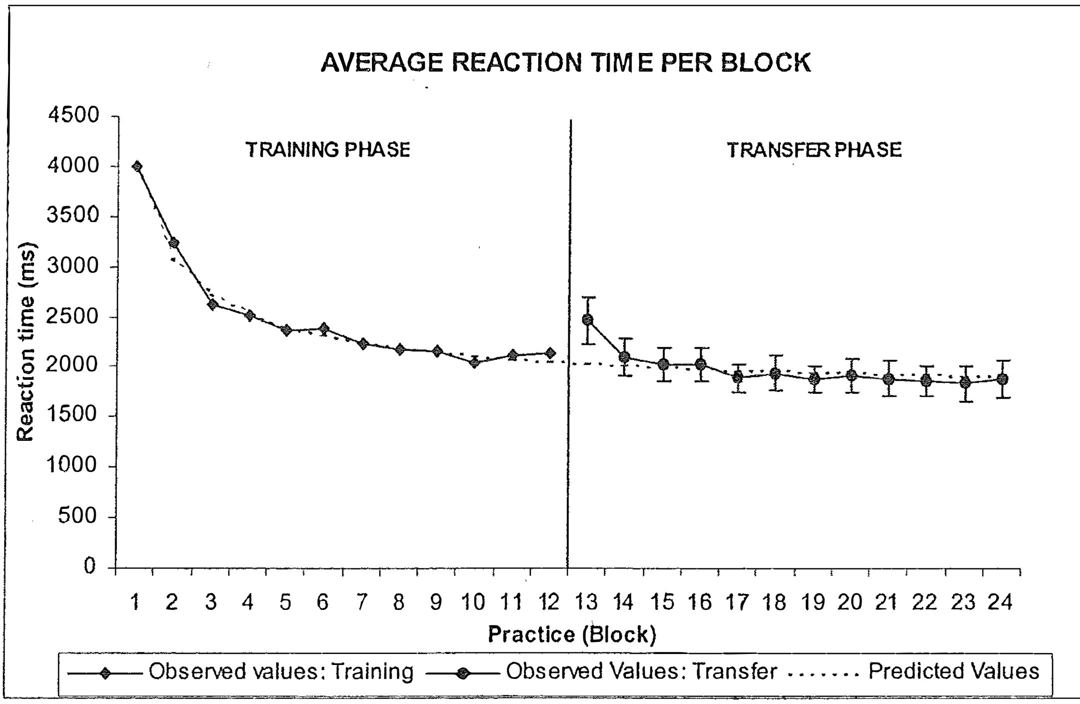


Figure 3. The disruption of transfer performance from predicated values as reported by Johnson (2005).

While Johnson's (2005) results provide strong evidence that contextual changes can significantly disrupt performance, the analysis of the disruption like those of Speelman and colleagues, focussed on mean reaction times at a block level. As a result, it is not known how this disruption is distributed on a trial by trial basis. Such research would enlighten the characteristics of disrupted performance due to contextual change, and may also be beneficial in respect to how Anderson and Logan's theories could be adapted to accommodate such findings.

Two broad possibilities exist as to the trial by trial nature of the disruption. Firstly the disruption may be isolated to the first multiplication trial following the contextual change, with performance returning to its predicted path by the very next trial. Such a result, while still contradictory to both the ACT and instance theory, could perhaps be accounted for by Logan and Anderson merely as a 'surprise' effect in which the participant is briefly distracted before gaining focus again.

The second possibility is that the disruption is broader in scope, and participants may require a number of trials before performance returns to its predicted path. Should this occur, both ACT and instance theory would be presented with a greater issue as the disruption could not be discounted as a fleeting 'surprise' effect. As such, the aim of the present study was to build upon the findings of Johnson's (2005) study, firstly by replicating the experiment, and secondly by examining how the disruption is distributed on a trial by trial basis.

Method

Participants

A total of 59 participants took part in the experiment, with 18 of the participants being recruiting from the school of psychology volunteers list, and the remaining 41 were from the general public. Those who were recruited through the school of psychology were given a raffle ticket to go into a $50.00 draw as an incentive. The participants were aged from 18-65 ($M = 36.19$, $SD = 15.24$) of which 19 were male ($M = 39.00$ years, $SD = 16.11$), and 40 were female ($M = 34.82$, $SD = 14.82$).

Design

The study employed a within-subjects design and examined the effect of context change on performance speed. Context change involved the change from addition problems to subtraction problems or vice versa for the second part of each trial. This change occurred after the participant had completed 12 blocks of trials (also known as the training phase).

Materials

A Power Macintosh G4 computer with the program Superlab was used to present stimuli and record response times. Each participant completed the task separately in a quiet room, with the task taking approximately 5-10 minutes to complete.

Procedure

This study was viewed and given approval by the Faculty of Computing, Health and Science Ethics Committee at Edith Cowan University.

When the participant began the task they were firstly asked a multiplication problem which was presented in the middle of the screen. The multiplication problem was randomly selected from one of six problems, and were identical to those used by Johnson (2005); namely 6 x 2, 6 x 3, 6 x 4, 6 x 7, 6 x 8 and 6 x 9. Once they had worked out the answer they were to then press the space bar as quickly as possible.

Two possible answers then appeared on the screen; one in each of the bottom corners. The participant was to then press one of two keys on the keyboard as quickly as possible which were highlighted with coloured stickers to make them more salient. The 'z' key on the bottom left of the keyboard corresponded to the answer on the bottom left of the screen, and the '/' key corresponded to the answer on the bottom right of the screen. The words 'correct' or 'incorrect' appeared on the screen following the participant's response.

The participant was required to remember the correct answer as they were then asked either to add or subtract a given number to it. This was the distractor task. Again this followed the design of Johnson's study and the six possible numbers that the participants were presented with included, 2, 3, 4, 5, 6, and 7. While the multiplication problem was always presented first, both the multiplication and addition/subtraction problems for each trial were selected randomly.

The combination of a target problem and distractor problem was known as a trial and six such trials constituted a block. For the training phase 12 blocks were presented. The transfer phase consisted of two blocks of the same design, however if the participant was given addition problems in the training phase, they were now given subtraction problems and vice versa. Half the participants were given addition problems as the distractor task while the other half were given subtraction problems for counterbalancing purposes.

Results

Reaction time was the dependent variable and was measured in milliseconds. Only correctly answered target problems were used and both the time taken to press the space-bar and select the correct response was used in the analysis. Only participants who had an accuracy rate of 80% or greater were included in the analysis.

For each participant, a mean reaction time was calculated for each block. For each block, an overall mean reaction time across all participants was calculated. This was then plotted to examine whether a power function of the form $T = bN^c$, would provide a good fit to the data. The parameters of the best fit power function are provided in Table 1.

Table 1

Parameters of the power function fitted to the reaction times of the Training data.

Parameters		Goodness of fit	
b	c	R^2	rmsd
4.10	-0.25	0.94	0.13

Note: rmsd = root mean squared deviation.

This best fit power function was then plotted with the training data and extrapolated into the two blocks of the transfer phase (See Figure 4). The power function fitted the data well, as is shown by the small root mean squared deviation (rmsd) value and large R^2 value.

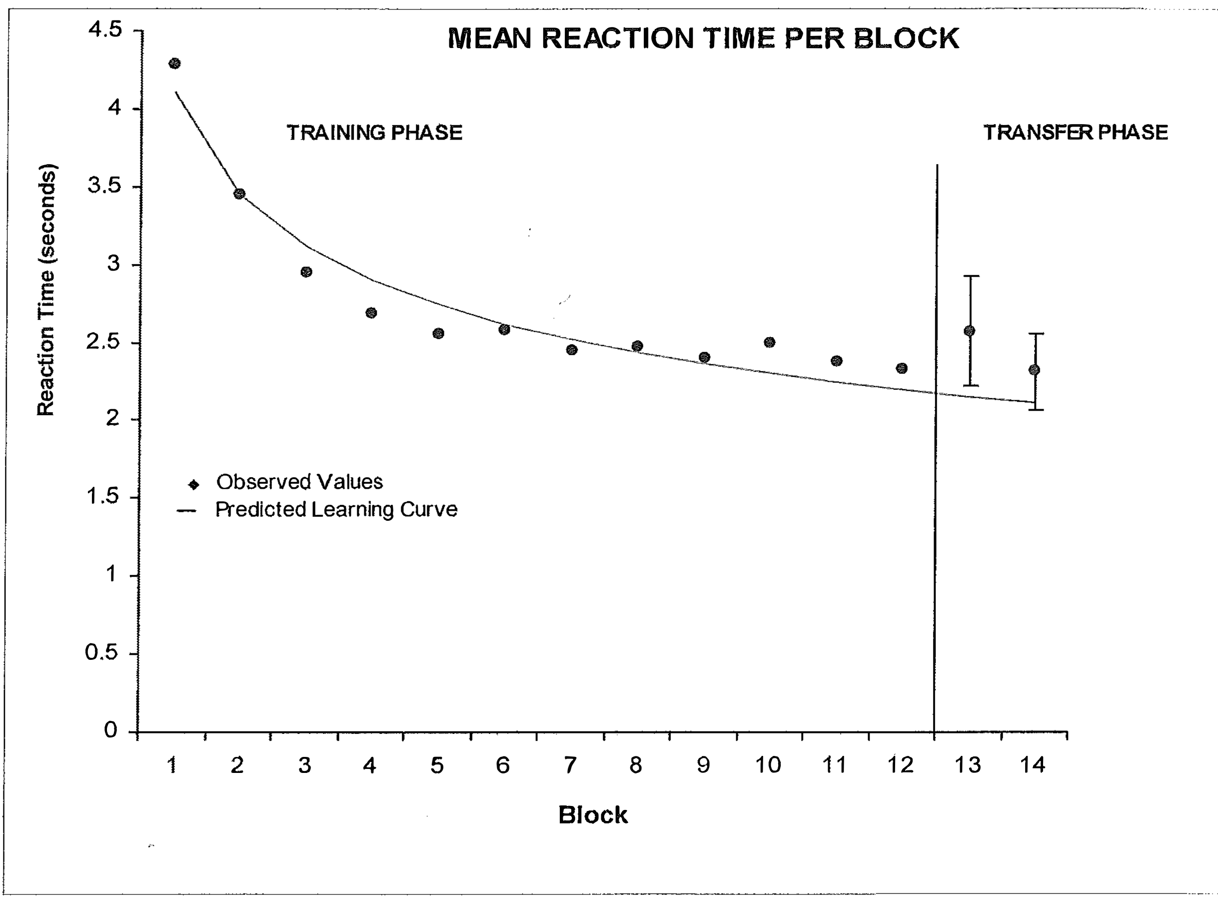


Figure 4. Mean reaction times for each block with a power function fitted.

It is also visually evident that there is a disruption in performance speed for block 13. This is supported by examining the 95% confidence interval bars for the two blocks in transfer in relation to the predicted learning curve.

To examine whether this disruption between block 12 and 13 was significant, a paired samples t-test was conducted. The results showed that block 12 ($M = 2.23$

seconds, *SD* = 0.93 seconds) was significantly faster than block 13 (*M* = 2.48 seconds, *SD* = 0.96 seconds), $t(58) = 3.17$, $p < .05$.

Given this finding, further analysis was performed on reaction time in block 13 on a trial by trial basis. This involved conducting five paired sample t-tests, comparing the first trial of block 13 against every other trial. A Bonferroni adjustment was made on the alpha level to control for an increase in Type 1 errors. The results showed that there was a significant difference between trial one (*M* = 1.93, *SD* = 0.53) and trial two (*M* = 2.62, *SD* = 1.19), $t(47) = 3.99$, $p < 0.01$, trial one (*M* = 1.92, *SD* = 0.50) and trial three (*M* = 2.20, *SD* = 0.79), $t(49) = 2.39$, $p < 0.01$ and trial one (*M* = 1.88, *SD* = 0.49) and trial four (*M* = 2.28, *SD* = 0.86), $t(49) = 1.95$, $p < 0.01$. No significant difference was found between trial one and trial five, and trial one and trial six.

To examine whether trial one was an unusually fast trial, a paired sample t-test was conducted in which trial one (*M* = 1.93, *SD* = 0.52) was compared to the previous trial (i.e., the last trial of the training phase), (*M* = 2.05, *SD* = 0.83). No significant difference was found between these two trials, $t(49) = 0.99$, $p > 0.05$.

The trial averages of both transfer blocks were also plotted to see how well they fitted a power function. The parameters of the best fit power function are presented in table 2.

Table 2

Parameters of the power function fitted to the Transfer trials.

Parameters		Goodness of fit	
b	c	R^2	rmsd
2.79	-0.95	0.86	0.06

The curve fitted the data well, as is evident from the small rmsd and the large R^2 values. This is seen in figure 5, whereby the mean trial averages are plotted, along with the best fit power function. This shows that while only the first three trials of block one following the context change are significantly slower then the trial prior to the change, there is a gradual return of performance across both the transfer blocks.

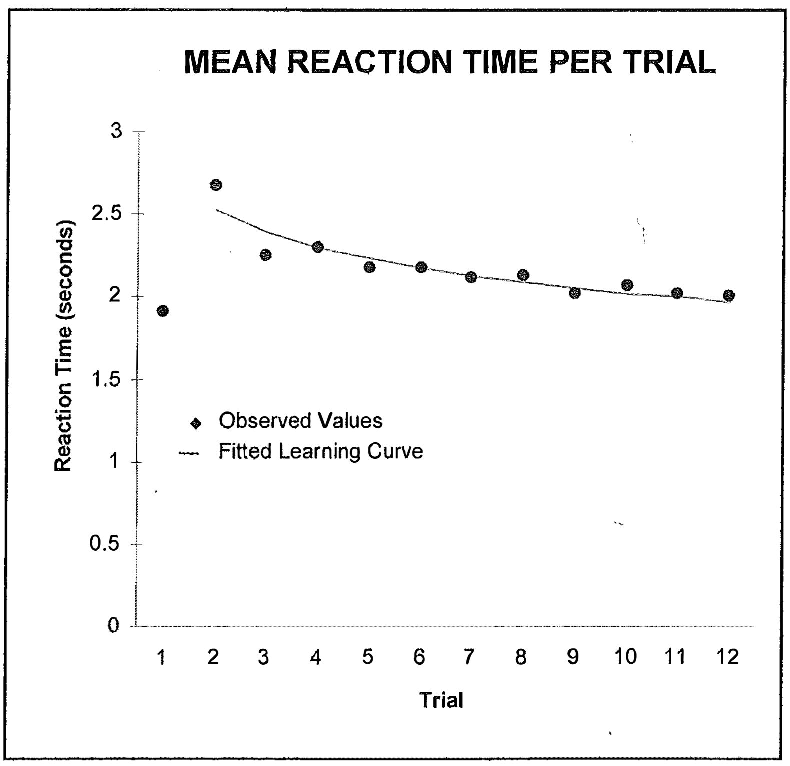


Figure 5. Mean reaction times for each trial with a power function fitted.

Discussion

Examining Figure 4 shows the means for each block plotted along with a learning curve which was fitted to the first 12 blocks, and the predicted learning curve for the two transfer blocks. A marked disruption on block 13 is evident. This is the first block in which the participants encountered the context change, and the results revealed this block was significantly disrupted. This disruption means the participant's reaction times slowed significantly, supporting the results obtained by Johnson (2005) and Speelman and colleagues (2001, 2004).

The finding of the disruption at the block level in itself contradicts both Anderson's and Logan's predictions regarding skill transfer. As both the training task and transfer task were being measured on the same items, Anderson would theorise that the same productions would be employed, resulting in complete transfer. This would be the same outcome predicted by instance theory, as Logan would posit that due to the identical problems, the instances that were created during the training phase would be utilised for the transfer problems, resulting in complete transfer. However given that the mean reaction time for the first block of transfer was significantly slower then the last block of the training phase, yet not as slow as the first block of the training phase, this means partial transfer has occurred.

Given this finding, further analyses were conducted to examine this disruption in more detail, specifically on a trial by trial basis. The aim being to see how this disruption is distributed. As each problem involved two components, with the multiplication problem always being presented first, the first trial of block 13 was used as a point of reference to compare against the other five trials in the block. This is because the contextual change is not presented until the second component of each trial, so for the first multiplication problem of block 13, the participants have yet to experience the context change.

The analysis showed that this disruption is more systemic and broad in nature, as the first three trials following the context change were significantly disrupted. The first trial was also compared to the previous trial to rule out the notion that trial one might have been unusually fast. However no significant difference was found between those two trials. As such, these findings discount the notion that the disruption may well have been a 'surprise' effect, whereby the participants quickly regain focus by the very next trial.

This is highlighted by examining Figure 5, whereby the means of each trial from both the transfer blocks were plotted, and a power curve function fitted. While the first three trials following trial one are significantly slower then this trial, visually it is evident that there is a gradual return of performance speed, further reinforcing the broad effect. This is also supported by examining the power curve function, which provides a good fit with the observed data.

While the disruption at the block level in itself contradicts both Anderson and Logan's theories, the finding that the disruption is broadly distributed presents even further issues, as it cannot be discounted as a brief momentarily distraction, instead these results suggest a more 'mental set' effect.

A mental set in this context can be thought of as the cognitive strategies that individuals use when solving a particular problem/s (Speelman Forbes & Giesen 2004: Woltz, Bell, Kyllonen, & Gardner, 1996). This notion stems from research that showed when people learn a particular task in a situation that is held constant, learning is assisted by this steady environment (Carlson & Yaure, 1990). It is theorised that when people can predict the next task, they can employ the processing rules that are being held in working memory and as such the task is performed more effectively.

Similarly, when a task is being learnt in a random environment, skill acquisition is hindered as people have to constantly reassess the task requirements, which involves interchanging processing rules into working memory. While a random task environment hinders skill acquisition, it facilitates skill transfer as the continual changing of tasks impedes the development of a mental set due to the processing rules being constantly changed (Carlson & Yaure, 1990).

In regard to the present study, the training task was of a particular repetitive nature as to promote a given mental set to develop, whereby the participants would have expected and predicted the following question. As such, these processing components would be kept in working memory in anticipation for the next problem. Subsequently, the mental set that would have been developed during the training phase would not be appropriate to use for the transfer phase, and would have required that the participants reassess the task.

The process of reassessing the task and engaging different processing rules means performance will be impeded. In the present study this is seen with a sharp decline in performance speed, followed by a gradual recovery. It is likely then, using the mental set paradigm, that when the participants were exposed to the transfer phase, they would have gradually developed a mental set in which those problems could be solved. This would have involved a different set of processing components being used and stored in working memory, which explains the gradual increase in performance for the transfer phase.

This study also highlights the sensitive nature that contextual change can have on a previously learned task. The task was carried out in controlled conditions, without distractions and with the distractor problems being of a very similar nature to the target problems, and yet performance was still significantly disrupted. It is likely then, that if this was conducted using more natural settings, the disruption would be even larger. Many real world situations involve the transfer of well learned skills with only a variation in context.

A more salient example of where this could be a factor is sporting teams who practise and develop skills in one location, and then have to play another team in a different location. The notion that teams often perform better when contextual matters are not altered has given rise to phrases such as 'home ground advantage' (Bray, Jones, & Owen, 2002). Another more common example may extend to people who learn to drive a car in a particular vehicle, and then drive in a different vehicle. While the task itself has not changed, as the context has, this may result in some disruption in performance which may gradually improve with the development of a new mental set. It is also likely that the longer the individual has spent developing a particular skill in a given constant context, the more ingrained the mental set, and the larger the disruption.

This notion that the same learned skills can be disrupted by contextual changes, and that this disruption is more then a fleeting distraction is incongruent with both the ACT* theory and instance theory. Both these theories exclude the role of context, and instead view skill acquisition through learning modules or learning components that function analogous to a machine; whereby a given input, or learning component is employed, and this results in a predictable output. However the results of the present study suggest while this description may provide a useful model of skill acquisition, if context is not taken into account a comprehensive explanation of skill acquisition will be incomplete.

This means that firstly, transfer performance cannot be predicted on the basis of training performance, and secondly that any theory attempting to make such predictions would need to take contextual factors into account. As such, further research can examine different tasks and their effects on contextual change, as well as examine the effects of skill transfer in natural settings.

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Appendix A

Information Letter and Informed Consent

Participant Information Letter

The purpose of the following research is to investigate how contextual changes can affect previously learnt skills. This research is being conducted by Matthew Parkinson under the supervision of Craig Speelman. It has been reviewed by and has received clearance from the Faculty of Computing, Health and Science Ethics Committee at Edith Cowan University.

As a potential participant in this study, please read the following:

1. The study you are about to participate in today will take approximately 30 minutes to complete. In this study you will be asked a series of simple number problems which will be presented to you on the computer screen. Do not panic if you have not done anything like this before as most of the other participants are in the same situation.

2. Your participation in this study is voluntary and you may withdraw from the study at any time, without penalty, by indicating to the experimenter that you do not wish to continue.

3. Your responses will remain completely confidential and your name will not be included in the records.

If you have any concerns resulting from your participation in this study, please contact Craig Speelman on 6304 5724. If you wish to discuss this research with an independent staff member please contact Dianne Mckillop on 6304 5736.

Appendix A

Informed Consent

I hereby agree that I have read and understood the participant information letter and agree to participate in the study outlined. I understand that all information gathered in this study will be used for research purposes only, and that my anonymity will be protected. I am aware that I may choose to withdraw from this study at any time without reprisal, and I can freely ask questions regarding the study. I also understand that this project has been reviewed and received clearance through the Faculty of Computing, Health and Science Ethics Committee at Edith Cowan University.

Name: ____

Signature: ____

Date: ____

Appendix B

Mean Block Reaction Times For Training and Transfer (seconds)

Participant	Training 1	Training 2	Training 3	Training 4	Training 5	Training 6	Training 7
1	5.8	4.27	2.91	2.91	2.53	2.5	1.55
2	5.03	3.94	4.14	4.14	2.61	3.68	3.23
3	4.7	2.45	2.12	2.12	2.24	1.87	1.67
4	3.22	2.14	2.31	2.31	1.84	1.7	1.9
5	3.72	4.11	4.17	4.17	2.26	3.32	2.63
6	5.8	4.27	2.91	2.91	2.53	2.5	1.55
7	5.42	4.13	3.53	3.53	2.61	1.87	2.47
8	3.66	2.11	2.52	2.52	2.02	1.86	2.16
9	2.19	2.15	1.53	1.53	1.66	1.75	1.66
10	3.79	2.81	2.53	2.53	1.89	2.09	1.78
11	3.43	3.81	3.76	3.76	3.48	3.64	3.28
12	6.3	4.2	2.75	2.75	2.37	2.32	2.48
13	2.32	1.73	1.68	1.68	1.77	1.91	1.67
14	1.25	1.3	1.18	1.18	1.15	1.25	1.25
15	2.54	2.17	1.78	1.78	1.79	1.54	1.43
16	4.13	4.66	2.6	2.6	2.29	3.44	2.68
17	3.18	3.07	3.82	3.82	2.58	2.52	3.12
18	4.02	3.41	2.75	2.75	2.84	2.8	2.28
19	2.28	1.2	1.53	1.53	1.38	1.04	1.23
20	4.11	6.47	4.51	4.51	3.76	3.33	2.81
21	3.56	3.51	2.88	2.88	2.68	2.62	2.82
22	8.01	5.12	5.21	5.21	4.42	4.64	3.17
23	2.2	1.29	1.92	1.92	1.7	1.63	2.04
24	2.67	2.08	1.84	1.84	1.71	1.68	1.47
25	3.55	2.7	2.33	2.33	2.06	2.13	2.22
26	3.08	2.3	2.68	2.68	2.91	2.26	2.32
27	6.25	6.73	4.54	4.54	3.67	3.39	2.93
28	2.97	1.9	2.18	2.18	1.72	2.48	2.32
29	5.21	6.37	4.11	4.11	2.01	1.7	2.58
30	4.33	2.71	2.14	2.14	2.01	2.29	2.43
31	2.98	3.1	2.28	2.28	1.96	2.05	1.84
32	2.46	1.72	1.66	1.66	1.22	1.77	1.39
33	4.07	4.18	2.96	2.96	2.29	2.02	2.18
34	2.4	1.95	1.66	1.66	1.59	1.47	1.59
35	3.15	2.17	1.53	1.53	1.54	1.85	2.17
36	9.73	6.58	3.45	3.45	2.67	2.95	2.57
37	4.41	3.33	2.69	2.69	2.21	1.93	2.77
38	3.6	2.69	2.47	2.47	2.07	1.93	1.82
39	2.7	2.59	2.71	2.71	1.89	1.6	1.81
40	3.07	4.02	2.81	2.81	2	1.78	2.01
41	5.47	7.05	5.25	5.25	4.49	5.69	3.03
42	11.02	5.68	6.02	6.02	6.46	7.03	5.95
43	8.05	6.99	7.97	7.97	5.73	7.55	7.98
44	3.15	2.73	2.17	2.17	1.93	1.61	1.5
45	6.96	2.31	1.83	1.83	2.59	1.93	1.54
46	5	3.49	3.05	3.05	3.35	3.05	3.09
47	2.7	2.18	1.89	1.89	1.69	1.7	1.5
48	1.91	1.96	1.76	1.76	1.63	1.83	1.59

49	3.96	2.51	2.99	2.99	2.67	2.34	2.32
50	3.13	2.49	2.23	2.23	1.86	2	1.88
51	12.15	6.15	4.89	4.89	4.06	3.64	4.32
52	2.86	2.1	2	2	1.89	2.04	1.82
53	6.04	5.77	4.97	4.97	3.12	2.66	2.96
54	6.92	5.56	3.71	3.71	4.78	3.9	4.41
55	2.61	2.56	2.21	2.21	2.29	1.98	2.54
56	3.4	2.55	2.16	2.16	1.54	2.09	1.73
57	3.83	4.67	3.49	3.49	2.82	2.36	2.39
58	2.27	1.77	1.9	1.9	1.95	1.98	1.78
59	4.39	4.09	5	5	5.77	5.74	5.17

Appendix B

Mean Block Reaction Times For Training and Transfer (seconds)

Participant	Training 8	Training 9	Training 10	Training 11	Training 12	Transfer 13	Transfer 14
1	2.1	1.65	1.74	1.83	1.72	4	1.67
2	3.01	3.14	2.3	2.7	2.36	2.3	2.35
3	2.19	1.96	2.86	1.98	1.94	2.26	1.87
4	2.12	1.81	1.63	1.59	1.81	1.82	1.72
5	2.69	1.77	1.7	2.58	1.74	1.87	1.82
6	2.1	1.65	1.74	1.83	1.72	4	1.67
7	2.55	1.73	2.15	2.38	2.41	2.21	2.66
8	2.92	2.2	2.58	1.6	1.85	2.19	2.1
9	1.87	1.55	2.08	1.58	1.85	1.61	1.82
10	1.56	1.83	2.25	2.05	2.33	2.6	1.82
	3.34	3.3	2.84	3.09	2.96	3.18	3.22
12	2.22	2.16	2.1	1.91	1.87	2.36	1.98
13	1.64	1.81	1.64	1.73	1.59	1.7	1.62
14	1.21	1.15	1.27	1.13	1.14	1.28	1.2
15	1.46	1.54	1.64	1.8	1.48	1.67	1.57
16	2.19	2.37	2.6	2.16	2.57	2.64	3.03
17	2.16	1.83	1.66	1.79	1.82	2.48	1.93
18	2.13	2.45	4.2	2.26	2.1	2.66	2.49
19	1.12	0.98	1.33	1.05	1.24	1.43	1.28
20	1.97	1.8	2.04	2.34	2.05	3.12	2.5
21	2.6	2.86	2.57	2.52	2.73	3.61	3.11
22	3.73	4.19	5.64	3.33	4.59	3.89	4.46
23	1.56	1.77	1.5	1.65	1.68	1.48	1.65
24	1.41	1.48	1.62	1.52	1.52	1.89	1.55
25	2.13	1.82	1.91	1.87	1.52	2.2	1.83
26	1.83	2.33	2.42	2.66	2.57	2.36	2.18
27	3.35	2.95	3.06	3.27	5.03	3.85	2.3
28	2.23	1.67	1.66	2.73	1.97	1.83	1.78
29	1.96	3.03	2.07	1.81	2.57	2.48	1.97
30	2.33	1.98	2.09	2.04	2.03	2.42	2.65
31	1.79	1.93	2.11	1.84	2.02	1.9	1.87
32	1.61	1.61	1.58	1.54	1.45	1.61	1.46
33	2.08	1.99	1.73	1.48	1.91	1.75	2.57
34	1.88	1.62	1.97	1.71	1.54	2.03	1.54
35	2.19	1.68	1.52	1.92	2.13	2.23	2.13
36	2.27	1.83	1.74	4.36	2.39	2.34	2.09
37	1.48	1.88	1.53	2.2	1.96	2.79	2.83
38	2.58	1.69	1.9	2.29	2.01	2.28	2.05
39	1.91	1.05	1.23	1.93	1.36	1.35	1.57
40	2.22	2.63	2.99	2.84	2.49	1.89	2.56
41	5.83	5.13	5.45	2.72	5.78	5.18	3.44
42	4.84	7.25	4.58	4.27	3.67	5.19	4.54
43	8.17	7.13	10.79	8.76	7.89		2.34
44	1.76	1.48	1.54	1.4	1.26	1.45	1.39
45	1.8	1.9	1.67	2.07	1.7	1.91	1.99
46	3.81	2.89	3.23	2.79	3.18	4.09	3.72
47	1.54	1.4	1.43	1.31	1.24	1.46	1.62
48	1.55	1.41	1.49	1.47	1.32	1.61	1.6
49	1.92	1.93	2.18	2.33	1.77	2.87	1.67

50	1.74	1.86	1.97	1.68	1.84	1.78	1.86
51	3.5	3.16	4.14	4.26	2.79	3.12	3.29
52	2.5	1.88	2.04	1.81	1.74	1.75	1.78
53	3.32	3.78	3.37	3.01	2.87	2.82	3.19
54	4.24	4.54	3.34	3.98	4.06	2.96	4.38
55	2.73	2.55	2.72	2.71	2.56	2.87	3.29
56	1.7	2.17	1.73	2.05	1.63	2.03	2.03
57	2.19	2.2	4.55	2.22	2.79	3.42	3.27
58	2.2	2.34	1.84	1.75	1.44	1.98	2.24
59	4.99	6.15	3.24	5.14	3.7	5.62	4.06

Blanks indicate outliers.

Appendix C

Mean Reaction Times for Transfer Trials (seconds)

Participant	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6
1	1.59		1.23			
2	2.13	2.77	3.05	2.14	1.87	1.79
3	3.31	2.08	1.42	2.14	2.77	1.9
4	1.68	2.02	2.15	1.79	1.8	1.49
5	1.52	2.5	1.67	1.54	1.94	2.04
6	1.59		1.23			
7	2.33	1.72	1.93	3.51	1.39	2.37
8	1.31	2.38	2.49	1.49	1.82	3.62
9	1.47	1.85	1.72	1.4	1.7	1.57
10	2.5	3.98	2.36	2.52	1.85	2.34
11	2.54	3.54	3.9	2.86	3.54	2.72
12	2.69	2.58	2.07	1.7	2.45	2.66
13	1.42	1.85	1.85	1.85	1.75	1.51
14	1.61	1	1.23	1.19	1.44	1.19
15	1.53	2.09	1.77	1.87	1.4	1.35
16	2.42	3.01	2.5	3	1.88	3.01
17	1.66	4.74	2.12	2.12	2.09	2.14
18	2.02	4.2	2.83	2.66	1.9	2.35
19	1.42	1.72	1.25	1.13	1.38	1.64
20	2.25	3.69	1.61	3.71	4.35	
21	2.88	3	2.94		3.58	3.11
22	1.55		4.57	3.68	2.89	2.52
23	0.96	2.06	1.18	2.5	1.27	0.89
24	1.55	1.76	2.16	2.11	1.8	1.95
25	1.78	1.92	2.57	2.55	2.35	2
26	1.88	3.58	2.42	2	2.38	1.91
27	1.69		3.83	4.32		3.19
28	2.78	1.44	1.51	2.18	1.11	1.84
29	2.21	2.56	2.53	2.08	1.76	3.71
30	2.39	3.39	2.21	2.79	2.07	1.65
31	1.67	2.49	2.81	1.56	1.74	1.73
32	1.17	1.42	1.46	1.84	2.12	1.63
33	1.49	1.52	2.21	1.97		1.57
34	2.33	3.59	1.8	1.41	1.46	1.53
35	2.03	1.39	1.94	2.09	2.59	3.35
36		1.41		2.27	1.35	1.85
37		2.35	3.28	2.9	2.33	3.06
38	1.97	3.01	1.89	1.84	2.24	2.64
39	1.13	1.38		1.75	1.26	1.24
40	1.46	1.98	2.35	1.77		
41		7.47	4.26	3.04	3.05	
42			1.8	1.9	2.17	
43		1.69				
44	1.33	1.47	1.26	1.57	1.88	1.19
45	1.69	2.98	1.7	1.84	1.82	1.46
46	1.93		4.23	1.8	3.33	3.63
47	1.71		1.47	1.5	1.4	1.23
48	1.43	1.99	1.52	1.87	1.25	
49	1.54	3.18		1.39	2.28	2.25

50	1.74	1.7	1.77	2.02	1.76	1.71
51	1.96	4.36	2.7	3.35	3.25	
52	1.82	1.68	1.73	1.5	1.74	2.01
53	2.82	2.77	2.49		4.11	1.92
54	2.59	2.73		4.02	2.75	2.75
55	2.32	3.11	3.09	2.93	3.37	2.4
56	2.69	2.38	3	1.83	1.2	1.08
57	2.15	4.53	2.97	2.72	1.7	6.45
58	1.75	1.21	1.51	3.88	2.09	1.42
59		3.04		1.71	1.77	

Blanks indicate incorrect responses.

Appendix C

Mean Reaction Times for Transfer Trials (seconds)

Participant	Trial 7	Trial 8	Trial 9	Trial 10	Trial 11	Trial 12
1	2.58	1.67	1.48	1.59	1.35	1.37
2	1.82	3.5	2.75	1.98	2.08	1.96
3	1.83	1.56	1.81	1.34	2.64	2.04
4	1.66	1.64		1.76	1.83	
5	1.77	1.75	2.06	1.8	1.65	1.88
6	2.58	1.67	1.48	1.59	1.35	1.37
7	1.61	3.19	2.51	1.64	3.92	3.06
8	1.89	1.69	2.87	1.73	2.55	1.89
9	1.44	1.53	1.79	1.37	1.71	3.11
10	1.68	1.92	1.47	1.73	1.93	2.22
11	4.51	2.67	2.53	3.5	3.34	2.79
12	1.66	2.47	1.61	2.55	1.74	1.85
13	1.65	1.65	1.44	1.71	1.72	1.54
14	1.16	1.31	0.99	1.41	1.24	1.05
15	1.27	1.66	1.47	1.88	1.49	1.77
16	3.54	1.86	1.87	2.1	2.08	
17	1.99	2.13	1.64	2.2	1.78	1.87
18	2.52	1.9	1.81	2.22	4.31	2.16
19	1.06	1.04	1.43		1.64	1.22
20	3.25	2.06	2.22	2.57	2.81	2.09
21	2	3.96	3.22	2.35	3.11	4.04
22	3.65		2.17	1.92		2.5
23	1.72	2.26	0.96	1.07	0.98	2.07
24	1.68	1.6	1.61	1.3	1.68	1.42
25	1.69	1.7	1.94	2.07	1.75	
26	2.35	2.23	2.66	1.75	2.07	2.01
27			2.87		2.21	
28	1.89	2.07	1.08	1.49	2.21	1.25
29	2.04	1.73	1.99	2.12	2.08	1.86
30		1.73	3.28	2.65	2.5	3.09
31	1.89	1.94	1.85	1.92	1.73	1.88
32	1.69	1.34	1.25	1.79	1.54	1.16
33	2.05	2.23	3.07	3.13	1.48	3.43
34	2.04	1.69	1.13	1.41	1.43	1.54
35	1.92	1.6	2.94	3.59	1.33	1.4
36	1.59	3.25	1.95	1.7	1.82	2.25
37	2.82	3.63		2.04		
38	1.73	2.08	2.33	1.83	2.63	1.7
39	0.97	1.3	0.98	1.36	3.12	1.69
40		2.14	2.97	2.14	2.09	1.47
41	3.03		2.06	4.37	3	2.7
42		2.87	2.27	1.9		
43	3.6					
44	1.61	1.26	1.26	1.37	1.63	1.25
45	2.09	1.47		2.8	1.61	
46	2.07	3	3.66		2.13	
47		1.41	1.31	2.61	1.44	1.32
48	1.54	2.33	1.54	1.57	1.35	1.29
49	1.15		2.29	1.54		1.71

50	1.62	2.28	2.07	1.59	1.88	1.75
51	2.85	2.84	2.08			3.87
52	1.87	1.66	1.85	1.87	1.57	1.87
53	2.69	5.21	2.26	1.78		2.75
54			3.68	2.44		1.96
55	2.61	1.81	2.2	3.04		2.16
56	2.79	1.93	1.62	2.61	1.98	1.24
57	2.17	3.54	2.35		1.61	2.81
58	2.88	1.59	1.62	3.62	1.88	1.85
59	2.47	1.81		2.42	2.05	

Blanks indicate incorrect responses.

Appendix D

Curve Fitting Data for Block Mean Reaction Times.

Block	Mean	Predicted Mean	Residuals
1	4.29	4.11	0.18
2	3.45	3.45	0
3	2.95	3.12	-0.17
4	2.69	2.9	-0.21
5	2.55	2.74	-0.19
6	2.58	2.62	-0.04
7	2.45	2.52	-0.07
8	2.47	2.44	0.03
9	2.4	2.36	0.04
10	2.49	2.3	0.19
11	2.38	2.25	0.13
12	2.33	2.2	0.13
13	2.57	2.15	0.42
14	2.31	2.11	0.2

Curve Fitting Data for Trial Mean Reaction Times (Transfer phase).

Trial	Mean	Predicted Mean	Residuals
2	2.67	2.53	0.14
3	2.25	2.39	-0.14
4	2.29	2.3	-0.01
5	2.17	2.23	-0.06
6	2.17	2.17	0
7	2.11	2.13	-0.02
8	2.12	2.09	0.03
9	2.02	2.05	-0.03
10	2.07	2.02	0.05
11	2.02	2	0.02
12	2.01	1.97	0.04