The effect of training mode on skill acquisition and transfer

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The Effect of Training Mode on Skill Acquisition and Transfer

Douglas F. Brewer

A Thesis Submitted in Partial Fulfilment of the Requirements for the Award of Bachelor of Arts (Psychology) Honours
Faculty of Health and Human Sciences, Edith Cowan University

30th October 1998
USE OF THESIS

The Use of Thesis statement is not included in this version of the thesis.
Abstract

This study examined the transfer of skills developed in solving a simple algebraic formula. Forty-two university Psychology undergraduates, randomly assigned to one of two training groups, were required to practice solving the formula \( \frac{x^2-y}{2} \) by substituting numbers for the variables \( x \) and \( y \). One group of participants practiced with eight sets of numbers, while the other group practiced with 16 sets of numbers. All participants performed 320 trials during training. In the transfer phase, the response times required to solve the same formula with a set of numbers not previously encountered was analysed to determine if the variation in training (a small or large set of numbers), affected the transferability of the acquired skill. Results indicated that partial positive transfer occurred, indicated by the response times for the transfer phase being significantly faster than the response times at the commencement of training, but not as fast as at the completion of training. Furthermore, transferability was a function of variation in training, indicated by participants who encountered a greater number of \( x \) and \( y \) stimulus pairs during the training phase being significantly faster on the transfer items than the participants who trained with a smaller number of \( x \) and \( y \) stimulus pairs. Results are consistent with the ACT* theory of skill acquisition, but present several difficulties for the Instance theory. Future directions and implications for the results of this study and how they can contribute to the development of more efficient training programs are also discussed.

Author: Douglas F. Brewer

Supervisor: Dr Craig Speelman

Submitted: 30th October 1998
Declaration

I certify that this thesis does not, to the best of my knowledge and belief:

(i) incorporate without acknowledgement any material previously submitted for a degree or diploma in any institution of higher education;

(ii) contain any material previously published or written by another person except where due reference is made in the text; or

(iii) contain any defamatory material.

Signed by (Douglas Brewer)
Date: 30.08.1998
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The Effect of Training Mode on Skill Acquisition and Transfer

Introduction

What advice can be given to a personnel manager confronted with the task of employing a mechanic to carry out warranty service repairs for a unique automotive company that embraces new orbital engine technology, when none of the prospective employees have had experience with that particular type of vehicle? Two candidates stand out from the others: one has had 20 years experience working for both Holden and Ford dealerships, the other has had 20 years experience working in a private repair shop servicing most common types of vehicles. Would one candidate be able to transfer their acquired skills to the unique vehicles more readily than the other? Do current theories on skill acquisition shed any light?

One view, epitomised by Logan’s (1988, 1990) instance theory, holds that skills are highly specific. That is, skills are restricted by the events experienced during training. Therefore, as neither candidate has specific experience involving the unique vehicles during training, neither would have skills to transfer to the new job. An opposing view, epitomised by Anderson’s (1982, 1983, 1987, 1992) ACT* theory, holds that skills are largely general in nature. That is, knowledge is abstract and can be applied beyond the experiences of training. Thus according to this view, one or both candidates may have skills that can be transferred. However, the question remains, which candidate would be better able to transfer their skills to the new task?

This study was designed to address this question. More specifically, the aim of the study was to determine the impact of the amount of variation during training on the transferability of the acquired skill. Before discussing the present experiment...
in detail, a brief review of the evidence supporting the major theories underlying skill acquisition and transfer will be undertaken. The transfer predictions of these theories were tested directly in the experiment that is the focus of this thesis.

In recent years, the interest in theoretical and empirical aspects of the transfer of skills has reemerged, as the nature of learning mechanisms underlying skill acquisition has been debated (for reviews, see Adams, 1987; Masson 1990; Singley & Anderson, 1989). These concerns have become increasingly important in a world where rapid technological changes often penalise those who are narrowly skilled and inflexible. Researchers have attempted to understand and predict the magnitude, direction, and locus of transfer throughout the present century, with many of the major arguments remaining unresolved (Pennington, Nicolich, & Rahm, 1995).

Thorndike (1906), Trowbridge and Carson (1932), Crossman (1959) and other associationists argued that when an individual encounters a new situation, they would benefit from previous experience in proportion to the number of overlapping stimulus-response associations that the old and new situations share. In contrast, Gestalt psychologists such as Judd (1908), Wertheimer (1945) and Gagné (1966) argued that for transfer of skills to occur between two situations, they must share a ‘deep structural relationship’. The essential elements of the Thorndike and Judd arguments can still be seen today, structured within the more powerful and precise vocabulary of the information processing paradigm of human cognition (Pennington, et al., 1995).

The modern version of Thorndike’s (1906) theory of identical elements is the theory of ‘common elements’ (Singley & Anderson, 1989), based on Anderson’s (1983) ACT* theory of skill acquisition. Conversely, the modern day parallel to Judd’s (1908) argument is Logan’s (1988, 1990) instance theory.
Anderson’s ACT* Theory

Anderson’s (1976) ACT (Adaptive Control of Thought) theory was based on a distinction between declarative and procedural knowledge and shadowed the three general stages Fitts (1964) suggested were involved in skill acquisition and development. The cognitive stage involves the initial encoding of a skill in a crude form sufficient to allow the person to perform the desired behaviour. It is a slow, deliberate process, mistake ridden, and resource intensive. Shiffrin and Schneider (1977; Schneider & Shiffrin, 1977) described this controlled process as being highly demanding of attentional capacity, usually serial in nature, and governed by the limits of the short term memory store. Verbal rehearsal of information required to perform the skill is frequently used in this stage. The associative stage involves refinement of performance. Initial errors due to misunderstandings, hesitancy, and unfamiliarity are detected and corrected resulting in a smoother performance of the skill. Verbal mediation is required less in this stage and begins to cease. The autonomous stage is where the skill gradually improves due to repeated performance. with this improvement often continuing indefinitely. According to Shiffrin and Schneider (1977; Schneider & Shiffrin, 1977), automaticity of behaviour occurs without the necessity for active control or attention, and because it is associated with long term memory, it is virtually unaffected by load.

In the ACT theory, the first stage, referred to as the declarative stage that corresponds to Fitts’ cognitive stage, the learner receives instruction and information about a skill, which is encoded as a set of facts about the skill. These facts can be used by general interpretive procedures to generate behaviour. In the second stage called knowledge compilation, that parallels Fitts’ associative stage, knowledge is gradually converted from declarative to procedural form. Finally, in the procedural
stage, that is similar to Fitts' autonomous stage, there is a further tuning of the knowledge so that it will apply more appropriately, resulting in a gradual process speed up. Skill is attained as the task is continually performed in a consistent information-processing environment (Ackerman, 1992; Fisk, Ackerman, & Schneider, 1987; Schneider, Dunais, & Shiffrin, 1984; Schneider & Shiffrin, 1977; Shiffrin & Schneider 1977).

The conception of the relationship between declarative knowledge and procedural knowledge has changed since Anderson's original ACT theory (1976) and his subsequent ACT theory (1983). In Anderson's (1993) current version of ACT called ACT-R (Adaptive Control of Thought – Rational), the emphasis has been shifted from declarative memory for instructions to declarative memory for examples of how the procedures should be executed. It is argued by Anderson (1993) that initial use of these examples involves analogy and that production rules are compiled that summarise the analogy process. Declarative knowledge does not need long-term memory status as originally implied, but is simply required to be active in working memory during the analogy process (Anderson & Fincham, 1994).

Declarative knowledge is conceptualised by Anderson (1982, 1983, 1987, 1993) as a statement of fact or semantic proposition (for example, a red traffic light means you should stop). However, it is flexible in its usage, as it can be applied to any relevant situation, but it is slow and effortful in its application. As interpretation and modifications of declarative knowledge take place, procedural knowledge is developed (for example, if a traffic light is red then stop). A production rule is generated as a by-product, which captures the essence of the solution and generalises across irrelevant features in both the source and target (Singley & Anderson, 1989). Productions, the basic unit of procedural knowledge, are if-then statements or
condition-action pairs such that when the ‘if’ condition is matched with the appropriate information in working memory, a particular cognitive or motor action is performed – the ‘then’ component (Anderson, 1982: 1987). Productions are akin to processing instructions, hierarchical goal structures that organise problem solving, which, when combined efficiently, lead to skilled behavior.

The acquisition of skill, according to the ACT* theory, results from the culmination of composition, proceduralisation and strengthening. Performance is enhanced by reducing the demands made on working memory, resulting from composition and proceduralisation, while strengthening improves performance by increasing the weight of associations between representations in memory.

Composition is the collapsing of a series of productions into a single, more efficient production that has the same effect as the sequence (Anderson, 1987). Component processes are merged, or “chunked” (Newell & Rosenbloom, 1981; Rosenbloom & Newell, 1986) together into fewer and larger knowledge structures that can be processed both faster and more efficiently than the original component processes (Fitts, 1964; Newell & Rosenbloom, 1981; Singley & Anderson, 1989).

For example, consider the following productions described by Speelman and Maybery (1998) for solving an equation such as $8 = 3x + 2$:

P1: \begin{align*}
  \text{If} & \quad \text{goal is to solve for } x \text{ in equation of the form } a = bx + c \\
  \text{Then} & \quad \text{set as sub-goal to isolate } x \text{ on RHS of equation.}
\end{align*}

P2: \begin{align*}
  \text{If} & \quad \text{if goal is to isolate } x \text{ on RHS of equation} \\
  \text{Then} & \quad \text{set as sub goals to eliminate } b \text{ from RHS of equation} \\
  & \quad \text{and then to eliminate } c \text{ from RHS of equation.}
\end{align*}

P3: \begin{align*}
  \text{If} & \quad \text{goal is to eliminate } b \text{ from RHS of equation} \\
  \text{Then} & \quad \text{divide both sides of equation by } b.
\end{align*}

P4: \begin{align*}
  \text{If} & \quad \text{goal is to eliminate } c \text{ from RHS of equation} \\
  \text{Then} & \quad \text{add} - c \text{ to both sides of the equation.}
\end{align*}
P5  \textbf{If}  \hspace{1em} \text{goal is to solve for } x \text{ in an equation and } x \text{ has been isolated on the RHS of equation}  \\
\textbf{Then} \hspace{1em} \text{LHS of equation is solution for } x.

The new hybrid production, P6, that results from the composition of productions P1 - P5, and that does the same work as the sequence but in less steps, would be:

P6:  \textbf{If}  \hspace{1em} \text{goal is to solve for } x \text{ in equation of the form } a - bx + c  \\
\textbf{Then} \hspace{1em} \text{subtract } c \text{ from } a \text{ and divide the result by } b \text{ and the result is the solution.}

Proceduralisation is the process that eliminates reference to declarative facts by building into productions the effect of that reference. Proceduralisation actually describes the development of productions P1 - P5 from a set of verbal instructions. This process involves domain specific information (productions) being integrated into an otherwise item-general production, thereby eliminating the need to hold declarative and analogy information in working memory (Anderson, 1983, 1993). Proceduralisation is analogous to McLeod, McLaughlin, and Nimmo-Smith's (1985) notion of information encapsulation (Brown & Carr, 1989). If the above productions P1- P6 were continually applied to a bank of problems that contained the same formula but different values for $a$, $b$ and $c$, then the following specific production would result from their composition:

P7  \textbf{If}  \hspace{1em} \text{goal is to find } x  \\
\textbf{Then} \hspace{1em} x = a - c \div b.

While composition exploits consistencies of operations, proceduralisation exploits consistencies of information operated upon (Brown & Carr, 1989).

Restructuring of productions due to composition and proceduralisation does not eliminate the original productions. Therefore, two or more productions may apply to a specific condition. However, when two or more productions compete, the
most specific production will prevail (Anderson, 1982, 1987). For example, consider
the following pair of production:

\[
\begin{align*}
    \text{If} & \quad \text{green arrow is indicated at traffic lights} \\
    \text{Then} & \quad \text{proceed to turn right} \\
    \text{If} & \quad \text{turning right} \\
    \text{Then} & \quad \text{give way to oncoming traffic}
\end{align*}
\]

The first production is more specific than the second production, and would therefore
apply when an intersection is controlled by traffic signals.

Furthermore, in keeping with the principle that hierarchical control of
behaviour is derived from the structure of problem solving (Newell, 1980), the ACT*
system specifies a hierarchical goal structure that sets the direction and organises the
problem solving task (Anderson, 1982). These goal structures control behaviour by
structuring the learning resulting from knowledge compilation. They serve to
indicate which part of the problem solution belong together and can be compiled into
new productions (Anderson, 1987).

The composition and proceduralisation of productions in ACT* is similar to
Cheng's (1985) reinterpretation of Schneider and Shiffrin's (1977) visual search data
in terms of a process she referred to as restructuring. According to Cheng, the
changes in performance that occurred when visual search tasks were practiced under
conditions of constant mapping were best explained by the emergence of a new
processing algorithm that followed a different and more efficient sequence of steps
than the original algorithm.

In addition to the reduction in performance time that comes from composition
and proceduralisation, skill acquisition is also enhanced by strengthening due to
practice. Productions accrue strength in memory with each successful application,
and lose strength or are weakened, each time they are unsuccessfully applied. The
stronger a production is, the faster it will be retrieved and executed (Anderson, 1982). Compared to the restructuring processes of composition and proceduralisation, strengthening produces a much less rapid improvement (Anderson, 1982). According to Anderson (1983), strengthening determines the rate of skill acquisition when the asymptote of the learning curve is approached, because at this juncture it is the only source of further improvement, composition and proceduralisation having been completed.

Anderson (1982) has demonstrated how the combination of these refinement and strengthening processes can account for the classic power-functions that characterise learning curves. Newell and Rosenbloom (1981) refer to the fact that performance speed improvements associated with human learning can almost always be described by power functions. The equation for a power function is:

\[ RT = a + bN^c \]

where RT is the response time to carry out the task, \( N \) is the number of practice trials, \( a \) is performance time at asymptote, \( a + b \) is the time on trial 1, and \( c \) is the rate of learning. This ubiquitous quantitative law of practice holds that by plotting the logarithm of time to perform a task against the logarithm of the trial number, a straight line, more or less, will always result. The power-function of learning has been repeatedly confirmed in empirical studies ranging from general problem solving (Neves & Anderson, 1981), fact recognition (Pirolli & Anderson, 1985), lexical decision (Kirsner & Speelman, 1996), to syllogistic reasoning (Speelman, 1991).

Anderson (1992) claimed that the ACT* theory could account for most of the commonly described features of automaticity such as those described by Schneider and Shiffrin (1977; Shiffrin & Schneider 1977). According to this view, much of the implicit nature of some forms of expertise may result from the automatic application
of knowledge that was previously explicit (Speelman & Maybery, 1998). With practice, compilation of declarative knowledge into procedural knowledge results in very efficient and fast productions that are not available to verbal description (Singley & Anderson, 1989).

According to the ACT* theory, practice can result in general and specific skills. Performance improvement results from changes in the representation of the algorithm that underlies performance. Productions represent an abstract algorithm for performing a task. Therefore, they may apply to task episodes that have not been previously encountered provided the algorithm they represent is appropriate (Speelman & Kirsner, 1997). Consequently, performance can improve in situations where there is little or no repetition of task events (Anderson, 1987, 1993; Carlson & Lundy, 1992; Corbett & Anderson, 1992; Frensch, 1991; Pennington, et al., 1995; Speelman & Kirsner, 1997).

The ACT* theory also holds that transfer between tasks is a function of the number of shared productions; that is, the more productions involved in performing one task that can be shared by the performance of another task, the greater the transfer. Therefore, it follows that transfer from one task to another similar task that is performed with the same strategy should be high, although not necessarily complete. According to Anderson (1987), the precise degree of transfer is difficult to calculate since the actual productions in use are not available to verbal report and are therefore subject to speculation. As Carlson and Schneider (1989) pointed out, this makes it very difficult to falsify the ACT* theory, as it can account for any degree of positive or negative transfer. However, transfer between tasks on the bases of common procedural knowledge has been consistently supported by empirical study (Anderson, 1982, 1987; Anderson & Fincham, 1994; Carlson, Khoo, Yaure, &

Logan's Instance Theory

A alternative to the ACT* process-based approach is a theory that relies on a strategy shift from algorithm-based to memory-based performance. This strategy shift is held to be responsible for speedup in skill acquisition, in lieu of improvement in the algorithmic process due to composition and proceduralisation. Logan’s (1988,1990,1992) Instance Theory of Automatisation is based on three assumptions. Firstly, it assumes that encoding into memory is an obligatory, unavoidable consequence of attention to a stimulus. Secondly, that all available information associated with a stimulus is similarly retrieved from memory as an obligatory, unavoidable consequence of attention. Thirdly, it assumes that each encounter with a stimulus is encoded, stored, and retrieved separately, even if it is identical to the previous encounter. It is this last assumption that makes the theory an instance theory of memory. These assumptions imply a learning mechanism – the accumulation of separate episodic traces with experience – that produces a gradual transition from algorithmic processing to memory-based processing. This process is similar to the transition process described by Seigler (1988) in his study of the acquisition of multiplication skills in children. Logan (1988) reviewed evidence for these three basic assumptions, while Boronat and Logan (1997) and Logan and Etherton (1994) confirmed the role of attention in both encoding and retrieval.

Furthermore, the instance theory also assumes that all sets of instances relating to a particular stimulus have the same distribution of retrieval times, that
memory retrieval time is a random variable, and that each memory instance and the algorithm are assumed to compete in a ‘race’ for control, in parallel and independently on each trial (Logan, 1988). The process that finishes the race first controls the response. Each memory trace is assumed to be retrieved separately and independently, so that with practice, more traces enter the race. The memory strategy eventually dominates the race as practice proceeds, because as more memory episodes accrue, the probability that one of them will win the race steadily increases (Rickard, 1997).

Logan (1988) has described the power-function speed-up, discussed earlier, as the first and most basic test of any performance model. The instance theory predicts a power-function (Borrorat & Logan, 1997). Logan (1988, 1992) and Logan and Etherton (1994) have shown that the power law applies to the entire reaction time distribution, not just the means, and that the shape of the learning curve is predicted from the shape of the underlying distribution of memory retrieval times.

The instance theory relies solely on memory recall in its account of skill acquisition. Unlike the ACT* theory, it does not involve any qualitative changes to the structure of stored knowledge. Therefore, the speed-up in performance indicated by a reduction in retrieval times is due to a faster instance being located in memory and winning the ‘race’. According to Logan’s theory, instances relating to a situation can be placed anywhere on a distribution of retrieval times. The greater the number of instances in memory, the faster one of these is likely to be retrieved. What makes one of these instances faster than another is not explained by Logan, but he implies that chance is responsible (Logan, 1988).

The power-function characteristics of the instance theory evolve from Logan’s (1988) suggestion that instances form a distribution of retrieval times similar
to a normal distribution curve. As the number of instances accumulate due to practice, the chance of retrieving an instance in less time than previously also increases. However, as Logan (1990) emphasised, it is the nature of such distributions that the movement in the tails of the distributions is a negatively accelerated function of the number of instances in the distribution. Therefore, at the commencement of the acquisition of a skill, performance is slow due to the use of an algorithm. As the skill develops, performance speeds up as instances are retrieved from memory (Compton & Logan, 1991). Finally, as the performance speed approaches the asymptote of the learning curve, the likelihood of retrieving a faster instance from memory decreases.

In contrast with Anderson's ACT* theory, Logan's instance theory predicts zero transfer between similar tasks. Because each encounter with a stimulus is stored individually, with great specificity, and as a whole, it follows that intermediate operations and representations between exposure to the stimulus and the final response are unimportant. Therefore, in encountering a new problem, no instance would exist in memory since no prior contact with that specific problem had occurred, and furthermore, prior practice on problems that were similar in general structure would also have no effect (Greig & Speelman, in press). Logan's instance theory has been described as 'all or nothing' and 'winner takes all'. Hence, instances are either totally useful, if recalled in the performance of a task, or they are useless if not recalled (Speelman & Kirsner, 1997).

Although the instance theory has successfully accounted for a wide variety of automaticity findings, ranging from locating targets in word displays (Bornat & Logan, 1997; Logan & Etherton, 1994), alphabet-arithmetic tasks (Compton & Logan, 1991; Logan, 1992) to lexical tasks (Logan, 1988, 1990), there are two
fundamental limitations in its current formulation. Firstly, as acknowledged by Logan (1988; see also Lassaline & Logan 1993), there is no notion of similarity-based retrieval; the only instances entering the race are those that are identical to the presented stimulus. According to Logan (1992) this assumption was largely made for simplicity and mathematical convenience. Secondly, as a race model, only the first instance retrieved drives the response. As Palmeri (1997) stated, there exists no possibility for a 'response competition' to emerge, whereby positive evidence for one response causes negative evidence against all other responses. The instance theory has been extended to account for these shortcomings by Rickard's (1997) CMPI theory, and Palmeri's (1997) BRW theory, which are reviewed later in this report.

In an attempt to clarify the theoretical difference between the ACT* and Instance theories, Anderson, Fincham and Douglass (1997) designed a series of experiments to evaluate the roles that exemplars and production rules play in the acquisition of cognitive skill. Participants were required to memorise eight examples that typified different rules. They were then required to extend those rules to new examples over several days. Results indicated that participants used a mixture of four strategies: Analogy to examples, where the memorised example was retrieved and analogically extended to the current problem; declarative abstractions, where the rule associated with the type of problem was consciously identified and applied after several applications; production rules, where participants developed a procedural embodiment of the rule after extensive practice; and retrieval of examples, where the memorised example matched the target problem and the answer was simply recalled. Anderson et al. concluded that performance in a skilled task is a complex mixture of processes. It involves the use of examples for both analogy
and simple retrieval purposes, and the use of rules for both abstract declarative and procedural purposes.

Transfer of Skill

The issue of transfer of training from one task to another is fundamental to theories of skill acquisition and is the focus of the present study. Transfer has been observed in tasks ranging from social judgements (Smith & Lerner, 1986), letter search (Schneider & Fisk, 1984), to lexical decisions (Kirsner & Speelman, 1993). Transfer has been defined by Pennington, et al. (1995) as "the use of knowledge or skill acquired in one situation in the performance of a new, novel task" (p. 176). Perhaps the dominant substantive issue in transfer research has been whether transfer is specific and limited in scope or whether it is general and ranges across diverse tasks and disciplines. To determine whether skills are general or specific, transfer of performance to a new task must be examined.

Three types of transfer have typically been identified (Anderson, 1987). Positive transfer occurs when previous experience facilitates performance of a new task. Negative transfer occurs when experience hinders performance of a new task. Zero transfer has occurred when previous experience has no effect on performance of a new task. Anderson (1987) argued that negative transfer may in fact be a form of positive transfer of inappropriate knowledge. Therefore, in this report only positive and zero transfer will be considered. Positive transfer may range from partial to complete transfer. Partial transfer occurs when previous experience results in some time savings on a new task, as compared to complete transfer that occurs when the response time for the new task is identical to the response time for the previously experienced task.
As stated previously, both the ACT* theory and the instance theory are specific about the nature of transfer; however, the conditions that foster transfer in the ACT* theory are considerably more liberal than those described by the instance theory (Speelman & Kirsner, 1997). The ACT* theory can account for any transfer on the continuum between zero and complete (positive) transfer. According to ACT*, the degree of transfer is directly proportional to the degree of overlap between the production rules acquired during training and the production rules necessary for performing the transfer task. By contrast, the instance theory is restricted in being able to account for only zero or complete transfer. If there are instances available for performing a task, then complete transfer will result, as evidenced by performance time being at least as fast as the previous retrieval of an instance. If, however, there are no instances available for performing a task (i.e., when the task remains the same but the trial items are different), then there will be zero transfer, and performance time will be equivalent to that observed in the first performance of the original task (Speelman & Kirsner, 1997).

Logan’s instance theory, therefore, suggests that skills are highly specific to experience in that transfer is restricted to situations previously experienced, whereas Anderson’s ACT* theory proposes that skills are more general, describing how they can apply to situations beyond past experience. Speelman and Kirsner (1997) compared these two accounts of skill acquisition and transfer in their study that tested 128 university student’s ability to acquire and transfer their skill in solving syllogisms. Although the syllogisms had the same form throughout the experiment, and no syllogism was repeated, they could all be solved using the same strategy. In the training phase, participants were exposed to one of four conditions. The ABBC and BCAB syllogism types (where the letters correspond to the order of the elements
in the premises and conclusions) were presented in blocked, random, highlighted or alternating sequence. In the transfer phase, participants received 96 trials with the syllogism type in random order. Practice resulted in improvement of the task that resembled the power-law of learning. Different training conditions lead to different performance strategies, and complete transfer occurred in the random and alternating conditions, with partial transfer observed in the blocked and highlighted conditions. Speelman and Kirsner concluded that it was the nature of the learning environment that determines the nature of the resultant skill rather than the skill being inherently general or specific. This concurred with Kramer, Stayer and Buckley's (1990) speculation that transfer may be influenced by the number and or variety of exemplars experienced during training.

Explanation of Speelman and Kirsner’s (1997) results presented several difficulties for the instance theory, whereas generally they supported the ACT* theory. Firstly, improvement was demonstrated on a task that did not involve any item repetition. According to the instance theory this cannot happen. Secondly, different task training conditions led to development of different performance strategies, resulting in different performance times. The instance theory does not have a mechanism to account for a performance time difference that is coupled to improvement in the algorithmic process resulting from practice. Thirdly, as asserted by Speelman and Kirsner, the most critical problem for the instance theory was the observation of partial transfer. The theory cannot account for partial improvement in learning, or a disruption to learning that is associated with deficiencies in task knowledge, a participant either has the task knowledge or they do not. Instances are described as totally useful in the performance of a task or they are useless (Speelman & Kirsner, 1997). In their conclusion, Speelman and Kirsner postulated that, if the
instance theory was to be a viable theory of skill acquisition and transfer, instances need to be more abstract than defined by Logan and that the theory should allow instances to be retrieved when they only partially match stimulus conditions or the task goal.

Logan's theory does have some empirical support. For instance, the highly specific nature of transfer to new tasks has been demonstrated by Lassaline and Logan (1993; see also Logan & Klapp, 1991) using a numerosity judgement task. Spatial patterns of between 6 and 11 elements were presented to participants who were asked to judge the number of elements as rapidly as possible without sacrificing accuracy. Initially, response times increased linearly with numerosity, suggesting that participants counted each element in a pattern, reflecting algorithmic processing. After practicing on a fixed set of patterns for several days, there was no difference in response times as a function of numerosity, indicating that algorithms had been replaced by recall of instances from memory. To further rule out the possibility that participants had learnt general strategies for judging numerosities of any patterns, rather than recalling the numerosities of specific patterns from memory, Lassaline and Logan presented new patterns after 12 days of training. Response times for the transfer task were again found to increase linearly with numerosity, with the magnitude of response times nearly the same as they were at the commencement of training. The finding that there was no transfer to the new patterns of elements was consistent with Masson's (1986) observation of word identification transfer, which reported that skill was highly specific and occurred only when training and test instances shared common letters in the same case (upper or lower).

Similarly, support for item-specific learning resulted from the studies of Byrne (1984) and Byrne and Carroll (1989) who reported that adult participants who
were required to learn an orthography based on sub-phonemic features could only transfer their skill on the basis of individual grapheme-phoneme items. Participants consistently failed to learn the relationship between the shape and sound of the orthographies, pronouncing them correctly only if the specific item had been presented before. The absence of transfer of skill indicated that participants relied on memory for individual items.

However, not all studies designed to confirm the instance theory have been so supportive. Logan and Klapp (1991) used an alphabet arithmetic task to examine the predictions of the instance theory, and reported that during the transfer phase performance was not reduced to the level it was before training. Furthermore, Logan and Klapp also found that participants who practiced with a small set of items did not perform as well as participants who practiced with a larger set of items, when transferred to a final set of totally new items. Despite the instance theory predicting no transfer in this situation, Logan and Klapp did not discuss the anomaly in detail. Logan however, has been reported by Kirsner and Speelman (1996) to have considered the possibility that positive transfer may be accounted for through the modification of the instance theory: By allowing the general algorithm to change with practice, some item-general skills may be acquired that can be applied to new situations.

Logan and Etherton (1994) have perhaps laid the foundation for such a modification to exist within the basic hypotheses of the instance theory. In discussing the role of attention in constructing an instance, they asserted that attention constructs propositions, and instances are propositions. Propositions are not only important because they are discrete representations, but also because they represent co-occurrence in a natural way. Propositions are predicates with a truth
value, and a predicate is a relation that takes one or more arguments. The co-occurrence in such multi-argument relations can be expressed directly. For example, "the ball is on the table" expresses the co-occurrence of ball and table. Furthermore, as Logan and Etherton also point out, different propositions can express co-occurrence indirectly through reference to the same argument. For example, "the ball is on the table" and "the cup is on the table" imply the co-occurrence of ball and cup because they are both on the table. Therefore it follows that some knowledge about an experience with a ball and table can be transferred to an experience with a cup and table even though they are different instances. For example, if in placing the ball on the table, it is noticed that there is some spilt milk on the table, then, in a separate instance, when the cup is placed on the table, foreknowledge of the spilt milk could result in the cup being placed in a position on the table to avoid the spill. Although Logan and Etherton did not explicitly state this conclusion, they did however state that they had only begun to explore the implications of a propositional theory.

The challenge to extend the instance theory to account for the observed effects of stimulus similarity on acquisition of skill has been taken up by Palmeri (1997) and Rickard (1997). Palmeri extended Lassaline and Logan's (1993) study in order to demonstrate that transfer could be influenced by the similarity of new patterns to the original training patterns. Fine-grained effects of pattern similarity were observed by giving participants new patterns that were moderate or high-level spatial distortions of the presented patterns in addition to the old and new patterns that Lassaline and Logan had presented. Results indicated that at transfer, response times were faster for moderate-similarity patterns than for low-similarity patterns, and low-similarity patterns were faster than unrelated patterns. This indicated that
the specific nature of transfer in skill acquisition tasks could be influenced by the similarity of stored exemplars.

Palmeri (1997) used a general model of automaticity and categorisation, called the exemplar-based random walk model (EBRW) to understand and explain his results. The EBRW incorporates both Logan's (1988) instance theory and Nosofsky's (1986) generalised context model (GCM) of categorisation. As with Logan's instance theory, when an item is presented, exemplars race to be retrieved from memory. However, in the EBRW, all exemplars race to be retrieved with rates proportional to their similarity to the presented stimuli, and unlike the instance theory, in which the first retrieved instance drives the response, in the EBRW, each retrieval provides incremental evidence to drive a random walk. Once sufficient evidence is gathered, a response is triggered. The actual overt response is determined by a race between this memory retrieval process and an algorithmic or rule-based process.

Rickard (1997) introduced a component power laws theory (CMPL) that assumes that memory retrieval is strongly dependent on attention and that only one retrieval event can be completed at any given time. While it precludes parallel completion, it does not preclude parallel initiation of two or more memory-retrieval events. Furthermore, the type of memory that is assumed to be operating in the skill acquisition domain, according to Rickard, is best understood as a prototype representation for each item, which extracts and stores aspects of instances that are common across repetitions, and that are crucial for subsequent skilled performance. Practice therefore strengthens a prototype representation for each task. Unlike the instance theory, where the algorithm and instance retrieval processes are executed in parallel, the CMPL theory stipulates that either the algorithm or prototype
representation, but not both, are selected at the outset of each trial. However, although the CMPL theory may have greater explanatory potential than the instance theory, its major setback is the evidence for parallel processing established in Compton and Logan’s (1991) research where participants indicated that 24% of the time they chose to employ simultaneous counting and remembering to solve the task.

Kirsner and Speelman (1996) and Speelman and Kirsner (1997) argued that whereas Logan’s model provides a satisfactory account of performance when transfer is either complete or zero, it does not cater for the more complex, but in practice routine, situation where transfer is partial. Palmeri’s (1997) EBRW theory and Rickard’s (1997) CMPL theory represent attempts to address this shortfall in Logan’s instance theory. However, the major difference between the ACT* theory and instance theory accounts of the algorithmic processes still remains. Furthermore, the opening question as to which mechanic is more able to transfer the skills acquired during training to the new job is still unresolved. The ACT* theory, in contrast to the Instance theory, holds that knowledge is abstract and can be applied beyond the experience of training. However, like the EBRW and CMPL theory, the ACT* theory does not qualify what enhances the transferability of skill.

In an experiment designed to test the transfer predictions of general and specific theories of skill acquisition, Greig and Speelman (in press) randomly assigned 37 university undergraduates to one of two experimental conditions involving the solving of a simple algebraic equation in both a training and transfer phase. In the training phase, participants were exposed to 270 trials at solving the equation \( x^2 + 2y = A \), where each pair of values for \( x \) and \( y \) were encountered 30 times. In the transfer phase, the task involved another 270 trials at solving the same equation, but with nine new pairs of values for \( x \) and \( y \). Results indicated significant
positive transfer of skill to the new numbers, however it was not complete transfer, as performance was disrupted by the manipulation. That is, at the commencement of the transfer stage, response times (RT) were slower than the RT at the end of training, but not as slow as the RT at the commencement of training.

Greig and Speelman (in press) interpreted these results to indicate that skill acquisition is neither restricted to the specific task features experienced during training, but neither is it totally generalisable to new situations. They concluded that both general and specific learning provide substantial contributions to performance. According to the ACT* theory, because the same equation was used throughout, an item-general production was generated that could be applied to any set of \( x \) and \( y \) values. Similarly, because each pair of values for \( x \) and \( y \) was encountered 30 times, item-specific productions were developed that could be implemented in place of the item-general productions. During the transfer stage, the item-general productions developed in training could have been implemented, however, the item-specific productions acquired during training could not have been executed. Although improvement in general skills could account for some improvement in the RTs at transfer, it could not account for improvement to a level similar to that at the conclusion of training, if specific skills had been developed during the training phase. Item-specific productions involve fewer processing steps and are therefore quicker than item-general productions. When, however, the opportunity arose to develop new item-specific productions through further practice, RTs should have returned to pre-transfer levels. This prediction was confirmed by applying a power function that provided the best fit to the training data performance times, and extrapolating it to the transfer phase. The extrapolated training power function, as predicted, underestimated the performance time for at least the first half of the
transfer phase, but predicted the performance times for the second half of the transfer phase.

Logan's (1988) instance theory could also account for Greig and Speelman's results as the majority of the $x$ and $y$ values presented during training and transfer were the same, only arranged in different combinations, in the two phases. As a substantial proportion of the problem space was shared, considerable transfer could be predicted by a relaxed version of the instance theory (if it were possible to divide instances into separate components).

Speelman (in preparation) also used undergraduate university students to practice solving an algebraic formula $\left[\frac{x^2-y}{2}\right]$ to examine the transfer of skills between a training and transfer phase. The experiment was designed to overcome the limitations of Greig and Speelman (in press) that caused ambiguity in interpreting the results. This was achieved by having participants practice with one set (eight pairs) of values for $x$ and $y$, and then use a completely different set (eight pairs) of values for $x$ and $y$ in the transfer phase. Only the equation was common between the training and transfer phases of the experiment. In the training phase, participants were exposed to 64 trials with each set of values for $x$ and $y$ encountered eight times. Similarly, in the transfer phase, participants were also exposed to 64 trials with each new set of values for $x$ and $y$ encountered eight times. Participants were randomly assigned to one of two groups to allow the two sets of values for $x$ and $y$ to be counterbalanced to control for possible differences in difficulty between the two sets of items.

The results of Speelman's (in preparation) experiment mirrored those of Greig and Speelman (in press). That is, a significant positive partial transfer of the
skill acquired in solving the algebraic formula was transferred to the new set of values for $x$ and $y$. Similarly, the best-fit power function that described the training performance, when extrapolated to the transfer phase, underestimated the performance times for the first two thirds of the transfer phase. Results confirmed that both general and specific task features contribute to skill acquisition.

Although a relaxed version of the instance theory could explain Greig and Speelman’s (in press) results, the theory cannot explain Speelman’s (in preparation) results. There was no common ground shared between training and transfer other than the algebraic formula, therefore, only an item-general production for solving the formula for any given value of $x$ and $y$ could be carried forward into the transfer task. Furthermore, Logan (1988, 1990) deemed that each processing episode is encoded, stored and retrieved as a single, unique unit. The stimulus and response features of each episode are represented together in memory, without reference to relevant information such as component features of a task. Therefore, whether the race is between an instance and the algorithm or a prototype representation of an instance and the algorithm is of no explanatory value in understanding the partial transference of skill observed. In Speelman’s experiment there was no similar instance to recall or use to form a prototype, as the values for $x$ and $y$ were different in the training and transfer tasks.

The Current Experiment.

The current study seeks to address the unresolved question underlying the problem of which mechanic is more able to transfer the skills acquired during training to the new job. Speelman and Kirsner’s (1997) findings that different training conditions led to different performance strategies resulted in their
postulating that if training was highly constrained, such that few variations were experienced and reliance on past solutions was encouraged, highly specific skills would result. If training was less constrained, so that many task variations were experienced and the development of general strategies was encouraged, abstract skills that are highly transferable would result (cf. Kramer, Stayer, & Buckley, 1990; Logan & Klapp, 1991; Schneider & Fisk, 1984). Based on this view, the mechanic whose skill acquisition involved training with a greater number of vehicle types would be more able to transfer his skills to the new job.

The aim of the present study was to test the above prediction of Speelman and Kirsner (1997). The proposed study extends Speelman's (in preparation) experiment by using the same algebraic formula \( \frac{(x^2 - y)}{2} \) and manipulating the number of \( x \) and \( y \) stimulus pairs encountered during training (the independent variable). It is anticipated that if only a small number of \( x \) and \( y \) stimulus pairs are encountered during training, then participants will be encouraged to develop highly specific routines for performing the task. This will be reflected by the transfer phase response times (the dependent variable) being significantly greater for those participants who trained with fewer \( x \) and \( y \) stimuli pairs compared to participants who trained with a greater number of \( x \) and \( y \) stimuli pairs. Conversely, it is anticipated that if a large number of \( x \) and \( y \) stimulus pairs are encountered during training, then participants will be encouraged to develop more general routines for performing the task regardless of the items presented (i.e., they will develop skills that are more transferable to slightly different situations such as stimulus pairs not encountered previously).
An additional design feature of the present study was that all participants receive equivalent practice with the task, but different amounts of practice with particular items, similar to the practice manipulation in Experiments 1 and 2 of Logan and Klapp's (1991) study. Thus the experiment was designed to assess the extent to which practice with specific items affects transfer.

In Speelman's (in preparation) experiments, it was a necessary feature of the design that the transfer phase consisted of the same number of trials as the training phase. In this experiment, only one block of eight trials was considered necessary to test the transferability of skill. However, a second block of trials will be included, consisting of four \(x\) and \(y\) stimulus pairs from the training phase, and four \(x\) and \(y\) stimulus pairs whose \(x\) values have been encountered during training, and whose \(y\) values were encountered only during the transfer phase. This will allow the experiment to assess if the components of an instance can be individually useful in the transfer of skill. If the RT's for the mixed (old/new) items in the second block of the transfer task were significantly different to the RT's for the first block of the transfer task, then it could be assumed that some item-specific production for solving the value of \(x\) had been transferred.

Speelman and Kirsner (1997) have predicted that if training was highly constrained, highly specific skills would result, and if training was less constrained, abstract skills that are highly transferable would result. In view of their prediction, it is hypothesised that participants who encounter a greater number of \(x\) and \(y\) stimulus pairs during the training phase will have significantly faster response times in the transfer phase than participants who train with fewer \(x\) and \(y\) stimulus pairs. If the transfer response times are not significantly different to the response times at the commencement of training, then the transfer of skill will be zero. If however, they
are significantly different, then positive transfer can be assumed. Because the general skill of solving the algebraic formula is common to both the training and transfer phase, it is hypothesised that partial positive transfer will occur, indicated by the response times for the transfer phase being significantly greater than the response times at the completion of training, but not as great as at the commencement of training.
Method

Participants

Forty-two volunteer undergraduate psychology students from Edith Cowan University participated in this study, of which 34 were female and 8 were male. The participants' ages ranged between 17 and 48 years, with the mean age being 30.12 years. Participants were recruited by announcements during lectures, and randomly assigned to one of two experimental groups. There were 21 participants in both groups, with males and females equally distributed between the two groups. They were rewarded with a cup of coffee/tea and a Mars Bar upon completion of the testing session.

Design

The study measured the response time required to solve the algebraic formula \( \frac{(x^2 - y)}{2} \) in the training and transfer phase of the skill acquisition task. In the training phase, participants received one of two levels of the independent variable (number of pairs of values for \( x \) and \( y \)). One group was given eight pairs of values for \( x \) and \( y \) and the other group was given 16 pairs of values for \( x \) and \( y \). In the transfer phase, both groups were presented with new values for \( x \) and \( y \) not encountered in training.

Apparatus

An Apple Macintosh LC computer with a 13 inch monochrome monitor was used to present the task to the participants, collect their responses and record their response times. The computer software was custom designed using the HyperCard 2.3 programming language. The algebra equation used by Speelman (in preparation)
\[ \frac{(x^2 - y)}{2} \] was also used in the current experiment. Values for the \( x \) and \( y \) item sets (e.g., \( x = 5 \) and \( y = 9 \)), for the training and transfer phases are presented in Table 1.

Table 1: Values for \( x \) and \( y \) during the Training and Transfer phase, with appropriate odd or even response.

<table>
<thead>
<tr>
<th>Training Phase</th>
<th>Group One Participants</th>
<th>Group Two Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x ) ( y ) Answer Odd/Even</td>
<td>( x ) ( y ) Answer Odd/Even</td>
<td></td>
</tr>
<tr>
<td>5 9 8 E</td>
<td>5 9 8 E</td>
<td></td>
</tr>
<tr>
<td>5 11 7 O</td>
<td>5 11 7 O</td>
<td></td>
</tr>
<tr>
<td>5 13 6 E</td>
<td>8 2 31 O</td>
<td></td>
</tr>
<tr>
<td>5 15 5 O</td>
<td>8 4 30 E</td>
<td></td>
</tr>
<tr>
<td>8 2 31 O</td>
<td>9 13 34 E</td>
<td></td>
</tr>
<tr>
<td>8 4 30 E</td>
<td>9 15 33 O</td>
<td></td>
</tr>
<tr>
<td>8 6 29 O</td>
<td>4 6 5 O</td>
<td></td>
</tr>
<tr>
<td>8 8 28 E</td>
<td>4 8 4 E</td>
<td></td>
</tr>
<tr>
<td>5 13 6 E</td>
<td>5 15 5 O</td>
<td></td>
</tr>
<tr>
<td>8 6 29 O</td>
<td>8 8 28 E</td>
<td></td>
</tr>
<tr>
<td>9 9 36 E</td>
<td>9 11 35 O</td>
<td></td>
</tr>
<tr>
<td>4 2 7 O</td>
<td>4 4 6 E</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Transfer Phase</th>
<th>Groups One and Two</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Values</td>
<td>Old and New Values</td>
</tr>
<tr>
<td>( x ) ( y ) Answer Odd/Even</td>
<td>( x ) ( y ) Answer Odd/Even</td>
</tr>
<tr>
<td>6 10 13 O</td>
<td>5 9 8 E</td>
</tr>
<tr>
<td>6 12 13 E</td>
<td>5 7* 9 O</td>
</tr>
<tr>
<td>6 14 11 O</td>
<td>5 5* 10 E</td>
</tr>
<tr>
<td>6 16 10 E</td>
<td>5 15 5 O</td>
</tr>
<tr>
<td>7 1 24 E</td>
<td>8 10* 27 O</td>
</tr>
<tr>
<td>7 3 23 O</td>
<td>8 4 30 E</td>
</tr>
<tr>
<td>7 5 22 E</td>
<td>8 6 29 O</td>
</tr>
<tr>
<td>7 7 21 O</td>
<td>8 12* 26 E</td>
</tr>
</tbody>
</table>

* Denotes new values
**Procedure**

The task required participants to substitute values for \(x\) and \(y\) in the equation 
\[
\left(\frac{x^2 - y}{2}\right) = A.
\]
Each trial consisted of the presentation of the equation at the top of the computer monitor screen, with a single given value for each of the \(x\) and \(y\) variables in the centre of the screen. Participants were required to calculate the solution for the equation, and decide whether the solution was an odd or an even number. They were then required to register their decision by clicking with the mouse on the appropriate box (A is ODD or A is EVEN) located at the bottom of the screen. On screen instructions and layout of practice and trial tasks are presented in Appendix B.

Participants were randomly assigned to work one at a time, in one of two experimental conditions. They were fully informed of the procedure but not the purpose of the experiment prior to commencement (see Appendix A for Consent Form, and Appendix B for on screen introductions), and that they were free to withdraw at any time. They were instructed to work quickly through each set, pausing only between sets, emphasising that the goal was to respond as quickly as possible without sacrificing accuracy.

To allow the participants to familiarise themselves with the computer equipment and procedural format, two practice trials were presented in the format described above, with values for \(x\) and \(y\) that were not included in either the training or transfer phase. When the participants registered their answer to each practice trial, a box appeared in the centre of the screen indicating that the answer was CORRECT or INCORRECT – TRY AGAIN. After two practice trials, participants could choose to repeat the practice sets or proceed to the experiment by clicking on the relevant box on the screen (see Appendix B for practice instructions and screen layout).
In the training phase, forty blocks of eight trials each, a total of 320 trials, were generated by the computer in pseudo-random order, so that each pair of values for \( x \) and \( y \) were encountered only once per block. Each trial was presented on screen, one at a time in the format described above, without any indication of block grouping. When the participants registered their answer to each trial, a box appeared in the centre of the screen below the \( x \) and \( y \) values, for approximately three seconds, indicating that the answer was CORRECT or INCORRECT. The screen was then cleared of the trial task and feedback, and a new screen layout appeared giving the command to start the next trial when the participant was ready (see Appendix B for screen layouts and instructions). One group of participants (low variation group) was exposed to only eight pairs of values for \( x \) and \( y \) and was presented those item sets 40 times. The other group (high variation group) was exposed to 16 pairs of values for \( x \) and \( y \) (including the low variation group’s stimulus pairs plus eight others) and encountered those item sets 20 times during training.

Upon completion of the training phase, both groups received the same transfer task consisting of another two blocks of eight trials based on the original algebra formula. The \( x \) and \( y \) item sets in the first transfer block consisted of new values not encountered by either group in the training phase. The second block consisted of a mixture of old and new values for \( x \) and \( y \). This block included four of the \( x \) and \( y \) stimulus pairs from the training phase, and four \( x \) and \( y \) stimulus pairs whose \( x \) values have been encountered during training, and whose \( y \) values were encountered only during the transfer phase (see Table 1). The transfer trials were presented in the same manner as the training trials.

Participants responded to a total of 42 blocks of eight trials that took on average approximately 50 minutes to complete. There was no break between
training and transfer and no prior warning to participants that the range of values for the $x$ and $y$ stimulus pairs was going to change. However, participants were informed that they could pause or rest between trials if needed. Once the training and transfer exercises were completed, participants were debriefed, thanked for their participation and offered refreshments.
Results

The error rate for the last 10 blocks of training (trials 241 - 320) for each participant was scrutinised. Appropriate accuracy was deemed to be 70%, well above chance performance (50%). Results indicated that one participant’s accuracy was 61.25% in the last 10 blocks. The overall data set was analysed with and without this participant’s data, and revealed that deletion had no impact on the overall trend, therefore this person’s data was retained. The mean accuracy rate for all participants for the last 10 blocks of training was 93.41% (SD = 8.12). The reaction times from correct trials only were analysed.

Response time data in the training phase was analysed in 40 blocks of 8 trials each. The effect of the training condition was analysed using a 2 x 40 (Variation in Training x Practice) split plot analysis of variance (SPANOVA). The SPANOVA’s assumption of sphericity for the Practice effect was violated, therefore new degrees of freedom were calculated using a Huynh-Feldt value of 0.238. With an alpha level set at .05, there was a significant main effect for both Practice, $F(9,371) = 95.52, p = .000$, and Variation in Training $F(1.40) = 10.78, p = .002$. The interaction between Practice and Variation in Training was also significant, $F(9,371) = 2.27, p = .000$. Descriptive statistics are shown in Appendix C, and the interaction is illustrated in Figure 1.

The effect of the training condition on the reaction times for the last 10 blocks of eight trials were further analysed using a 2 x 10 (Variation in Training x Practice) split plot analysis of variance (SPANOVA). The SPANOVA’s assumption of sphericity for the practice effect was violated, therefore new degrees of freedom were calculated using a Huynh-Feldt value of 0.496. With an alpha level set at .05, there was a significant main effect for both Practice, $F(4,129) = 3.08, p = .001$, and
Variation in training, $F(1,40) = 11.09, p = .002$, indicating that the response times for the low variation group were significantly faster than the high variation group for blocks 31 to 40. Descriptive statistics are shown in Appendix C.

Figure 1. Mean response times as a function of the variation in the training phase (high variation/low variation) and practice (block) in both training and transfer phases. The two lines represent power functions that provide the best fit to the training data, and are extrapolated into the transfer phase (block 41).

Power functions of the form $RT = a + bN^c$ (where $N =$ number of blocks of practice), were fitted to the mean response times for each block in the training phase (parameters of these curves are presented in Table 1). In order to decide whether transfer performance constituted a significant deviation from the practice function observed during training, the power functions were extrapolated to predict perfect transfer performance. In addition, confidence limits ($\alpha = 0.05$) were calculated for
the mean response times in the first block of training (i.e., block 41). The power function and confidence limits are presented in Figure 1. If extrapolated performance falls within these confidence limits, transfer performance can be considered complete (Speelman & Kirsner, 1997). If extrapolated performance falls above the upper limit, transfer can be considered to be less than complete. In the present study, transfer was less than complete.

Table 1

<table>
<thead>
<tr>
<th>Type of Training</th>
<th>Parameters</th>
<th>Goodness-of-fit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td>Low variation training</td>
<td>1.00</td>
<td>12,314.92</td>
</tr>
<tr>
<td>High variation training</td>
<td>1.00</td>
<td>11,732.94</td>
</tr>
</tbody>
</table>

To examine the effect of variation in training on the transferability of skill, the mean response times for blocks 40 and 41 were analysed using a 2 (Block) x 2 (Variation in Training) split plot SPANOVA. The SPANOVA test assumptions, including homogeneity of covariance, were satisfactory. With an alpha level set at .05, there was a significant main effect for Block $F(1,40) = 147.16, p = .000$, and a significant effect for the Block by Variation in Training interaction $F(1,40) = 11.21, p = .002$. Tukey's HSD post hoc comparison tests indicated: a significant slowing of the response times between block 40 (training) and block 41 (transfer) for both the high variation group and the low variation group; that transferability is a function of the variability of the training task, indicated by the mean reaction times for the high
variation group being significantly faster than the low variation group, in block 41; and that there was no significant difference between the response times for either the low or high variation groups at the conclusion of training (block 40). Descriptive statistics are shown in Table 2, and the interaction is illustrated in Figure 2.

Table 2.

Mean Response Times (ms) of Training Block 40 and Transfer Blocks for Both Low and High Variation Training

<table>
<thead>
<tr>
<th></th>
<th>Low Variation Training</th>
<th></th>
<th>High Variation Training</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Training</td>
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A supplementary test was performed to investigate the relative slowing of performance for the low and high variation trained groups in moving to the transfer phase. By subtracting the response times for block 40 from the response times for block 41 for each participant, the difference between training and transfer response times were calculated. Data screening revealed an outlier for both the low and high variation training groups. Further investigation revealed that both participants had difficulty in calculating one of the transfer trials, but had recorded normal processing times on the remainder of the transfer trials. The average response times for both participants were recalculated with the outlying trial times omitted, and a repeat analysis of the data revealed no inordinate effect of these trials on the results. Both
outliers were therefore retained without transformation, as they were deemed to be part of their respective populations. Because the assumption of homogeneity of variance was violated, an independent $t$ test for unequal variance was computed, and found to be significant, $t(31.30) = 3.35$, $p = .002$. The mean difference between training and transfer response times for the low variation group was 5187 milliseconds ($SD = 2684$), compared to 2943 milliseconds for the high variation group ($SD = 1493$), indicating that greater variation during training results in less disruption when moving to the transfer phase and so indicates greater transfer of the acquired skill.

![Figure 2](image.png)

**Figure 2.** Mean response times at completion of training phase (block 40) and transfer phase (block 41), for low variation and high variation training groups.
To examine the effect of variation in training on the transferability of skill when only part of the transfer task was new, the mean response times for blocks 41, 42 old, and 42 mixed, were analysed using a 3 (Block) x 2 (Variation in Training) split plot SPANOVA. The SPANOVA test assumptions, including homogeneity of covariance, were satisfactory. With an alpha level set at .05, there was a significant main effect for the composition of the transfer block \( F(2,80) = 39.23, p = .000 \), and a significant interaction between block composition and variation in training \( F(2,80) = 6.48, p = .002 \). Tukey's HSD post hoc comparison tests indicated: a significant reduction in response times for both the high variation group and the low variation group, for block 42 old items, when compared to either block 41 or block 42 mixed; no significant increase in the response times between block 41 and block 42 mixed, for either the high variation group or the low variation group; and that transferability is a function of the variability of the training task when the transfer task includes new stimuli or partially new stimuli, indicated by the response times for the high variation group being significantly faster than the low variation group, in both block 41 and block 42 mixed. Descriptive statistics are indicated in Table 2, and the interaction is illustrated in Figure 3.
Figure 3. Mean response times for transfer items in block 41, 42 old, and 42 mixed, for both low variation and high variation training groups.
Discussion

Results of the current study supported the hypothesis that partial positive transfer would occur, indicated by the response times for the transfer phase being significantly faster than the response times at the commencement of training, but not as fast as at the completion of training. Furthermore, the results also supported the hypothesis that participants who encountered a greater number of x and y stimulus pairs during the training phase would have significantly faster response times in the transfer phase, when compared to participants who trained with a smaller number of x and y stimulus pairs.

These results concur with those postulated by Speelman and Kirsner (1997) and speculated by Kramer, Stayer, and Buckley (1990), suggesting that whether an acquired skill is specific to situations identical to those encountered during training or generalisable to other similar situations is determined by the nature of the skill acquisition. When only a small number of x and y stimulus pairs were encountered during training, participants were encouraged to develop highly specific routines for performing the task. This was reflected by the transfer phase response times being significantly greater for those participants who trained with a smaller number of x and y pairs. Conversely, when a greater number of x and y stimulus pairs were encountered during training, participants were encouraged to develop a more general routine that was useful for performing the task regardless of the items presented.

In the training phase, practice resulted in improvement of the task that reflected the power-law of learning (Newell & Rosenbloom, 1981), mirroring Greig and Speelman (in press) and Speelman’s (in preparation) findings with this type of task. Although there was no significant difference between the RTs for the high and low variation training groups at the completion of the training phase (block 40),
analysis of the last 10 blocks of training (blocks 31 - 40), revealed that the mean response time for the low variation group was faster than the mean response time for the high variation group. Furthermore, it appeared that while the low variation group were close to their asymptote, improvement in RTs was still occurring at the completion of training for the high variation group (see Figure 1). This is not surprising given that participants in the high variation training group were presented with each x and y stimulus pair 20 times during practice, whereas the participants in the low variation training group were presented with each stimulus pair 40 times during training.

Partial Transfer

The demonstration of partial positive transfer as illustrated by the training/transfer interaction in Figure 2 and confirmed by the extrapolation of the training power function into the transfer phase, as illustrated in Figure 1, supports the results of Greig and Speelman (in press) and Speelman (in preparation). However, as Greig and Speelman noted, explanation of the partial transfer is problematic for both general and specific theories of skill acquisition. Whereas general theories predict complete transfer between identical tasks with different items, specific theories predict zero transfer under these conditions. Therefore, as Greig and Speelman concluded, both general and specific learning must have contributed to the observed partial transfer.

As presented in the Introduction, Anderson’s (1983, 1987, 1993) ACT* theory can account for both general and specific skills resulting from practice, whereas Logan’s (1988, 1990, 1992) instance theory can only account for specific
skills acquisition. Therefore, the ACT* theory provides a superior account of the intermediate transfer observed in the present results.

According to ACT*, in the training phase of this experiment participants would have developed a set of productions specifically to solve the algebraic formula \( \frac{x^2 - y}{2} \). Initially these productions would be item-general processes in that they could be applied to any set of values for \( x \) and \( y \) substituted in the equation. However, some item-specific productions would develop by the end of training as each set of \( x \) and \( y \) values would have been encountered 20 or 40 times, depending on the training condition. These item-specific productions would only be executed in response to a particular \( x \) and \( y \) stimulus pair. Furthermore, as Greig and Speelman (in press) suggested, because these productions are more specific than the general set of productions, they would be more likely to be executed in response to a matching pair of \( x \) and \( y \) stimuli than a general set. They would therefore gain strength and eventually become faster overall with fewer processing steps, than the general sets. During the transfer phase, when new \( x \) and \( y \) stimulus pairs were encountered, the item-specific productions could no longer be implemented. However, participants would still be able to utilise their item-general productions. Hence, their performance during the transfer phase was slower than at the completion of training but not as slow as at the commencement of training, when no general set of productions had been developed.

According to Logan's (1988, 1990, 1993) instance theory, initial performance in the training phase of this experiment would be based on algorithmic processing with a gradual transition to memory-based processing as participants experienced further instances of the same \( x \) and \( y \) stimulus pairs. During the training phase, a race
would have occurred between the algorithm and the retrieval of each instance from memory. Gradually, as practice increased, item-specific instances would have been retrieved faster than the algorithmic process, thereby resulting in faster performance of the formula-solving task. However, during the transfer phase, when there were no prior instances to recall, participants would have had to rely on the algorithmic process to solve the formula. According to this view, the mean RTs for block 41 in the transfer phase should have been identical to the mean RTs for block 1 at the commencement of training, because no instances would have been available for the x and y stimulus pairs presented in this block, and algorithms do not improve with practice. However, this prediction was not supported by the current results. The finding of partial transfer is therefore in direct conflict with Logan's instance theory, and highlights the anomaly reported by Logan and Klapp (1991) that was unexplained. Furthermore, the partial transfer observed in the current results support Speelman and Kirsner's (1997) claim that if the Instance theory is to provide a viable account of skill acquisition and transfer instances need to be more abstract than suggested by Logan.

The propositional theory introduced by Logan and Etherton (1994) holds that instances are propositions, and as such are capable of expressing co-occurrences indirectly. It would appear that if this concept was used as a basis for modifying the instance theory, then information about one instance could be transferred to another similar but different instance. If applied to the present study, this view would allow information about the formula to be transferred indirectly by reference to the same argument. That is, because the formula is common to propositions that refer to the co-occurrence of the formula and some value for x and y, indirect transfer of information about the formula could result. This would lead to a type of subdivision
in instances, allowing part of an instance to be recalled from memory and applied to a similar situation (discussion of this issue follows, under section titled Transfer as a Function of Training Variation). However, because only information referring to the algebraic formula could be transferred, (as there would be no instances to recall that contain information relating to the new x and y stimuli values), only the algorithmic processing would be advantaged. That is, some modification to the algorithmic process, that results in a time savings could occur. According to the Instance theory however, the algorithmic process cannot be modified, it can only be displaced in the ‘race’ by an instance.

The application of the propositional theory to the transfer phase of the present study may hold strong power in explaining the partial transfer that was observed, however, it destroys the essence of the instance theory. That is, there would be no instances to join in the race with the algorithm – there would be no race – just a modification to the algorithmic process that results from information gleaned from a partially similar instance. Hence there is nothing to distinguish this account from that of the ACT* theory.

As previously discussed, Palmeri’s (1997) EBRW theory maintains that the specific nature of transfer in skill acquisition tasks can be influenced by the similarity of stored exemplars. Exemplars race to be retrieved with rates proportional to their similarity to the presented stimulus, with each retrieval providing incremental evidence to drive a random walk. Once sufficient evidence is gathered a retrieval is completed. The final response is determined by a competitive race between the random walk memory retrieval process and an algorithmic process.

In Palmeri’s (1997) transfer phase, moderate and low-level spatial distortions of dot patterns encountered during training were used that resulted in the RTs being
faster for both of these patterns than patterns which were unrelated. Although there was no similarity, in the present study, between the $x$ and $y$ stimulus values between the training and transfer phases, the formula was similar (the same). If the EBHW theory was applied to the present study, the partial transfer could be accounted for on the bases that the exemplars (consisting of the similar formula and new $x$ and $y$ stimulus values) were successful in their race with the algorithmic process, resulting in a savings in the RTs. However, on the basis of the ACT* theory, it could also be argued that there was no race, simply a modification to the algorithmic process due to composition and proceduralisation that resulted in the time savings. The partial transfer observed in the blocked and highlighted conditions of Speelman and Kirsner’s (1997) syllogisms study, where no exemplars were available for recall at the transfer stage, would seem to suggest that the latter argument cannot be dismissed.

Rickard’s (1997) alternative to the instance theory, the CMPL theory, replaces instances with a prototype representation in memory that extracts and stores aspects that are common across repetitions. The prototype, which is strengthened with practice, competes with the algorithm for a winner-takes-all selection at the onset of each trial. Furthermore, each step of the algorithm is assumed to be a single retrieval event. Therefore, the first retrieval event is crucial in determining the process, as it will be either the prototype recall or the commencement of the algorithmic process. When applied to the transfer phase of the present study, the CMPL theory, like the instance theory, would predict that the algorithmic process would be the winner, as no prototype would be available for recall to enter the race. Furthermore, although the CMPL theory, unlike the instance theory, can account for item-specific speedup with practice when the prototype is selected, it cannot account
for item-general speedup in algorithm execution when there is no prototype available. That is, if a prototype is available, it can compete with the algorithm at whatever step in the algorithmic process the competition applies. In this study, according to the CMPL theory, no item-specific speedup or item-general speedup should have been observed. However, the results suggest an item-general speedup in algorithm execution must have occurred to account for the time savings, in the absence of a prototype representation being available in memory. This is indicated by the RTs for the transfer phase being faster than the RTs at the commencement of training, but not as fast as at the completion of training. These results concur with Rickard's findings, that general speedup in algorithm execution did occur with practice. However, he suggested that the general speedup in his study could have resulted from participants referring to an algorithm example sheet during the commencement of practice but not at transfer.

The partial transfer observed in the present study was not subject to similar confounding practices of participants referring to examples as in Rickard's (1997) study. However, it might be argued that the participants, having practiced on 320 similar trials, were startled when confronted with new sets of x and y stimuli in the transfer phase. Participants were not informed of the nature of the experiment with respect to there being a training and transfer phase, nor was the introduction of the transfer phase indicated by the experimenter, as this was considered an important aspect of the design. To assess the possible effects of the unsuspected change in the stimuli, the old and mixed (old/new) stimuli were analysed separately for the second block of transfer trials. It would be reasonable to assume that any 'startle' effect would be extinguished by the second block of transfer. Results indicated that there was no significant difference between the RTs for block 41 and block 42 mixed, for
the low variation trained participants, or the high variation trained participants. This would suggest that there was no confounding due to a startle effect.

Transfer as a Function of Training Variation

The results of the present study indicate that participants who were exposed to a greater variation of stimuli during training had greater transferability of their acquired skill. This result supports Speelman and Kirsner's (1997) claim that "mechanisms underlying skill acquisition appear to be adaptive to the nature or the environment rather than fixed and only responsive to particular environments" (p.100, cf. Anderson et al., 1997; Kramer, Stayer & Buckley, 1990). These results also concur with Logan and Klapp (1991) who reported that participants who practiced with a small set of items performed more poorly than those who practiced with a larger set of items, when transferred to a set of new items.

Participants in the present study had the same amount of task practice, but differed in the amount of item practice, similar to the practice manipulation in Experiments 1 and 2 of Logan and Klapp's (1991) study. This feature of the present study has more relevance to everyday living, than the alternative of exposing participants to the same amount of item practice, but different amounts of task practice, that occurred in Logan and Klapp's Experiment 3. In the current economic climate, apprenticeships and study courses are being reduced, not extended in length of time. Therefore, it was considered important to standardise the task practice time in order to increase the generalisability of the results. Although Logan and Klapp reported that the learning rate depended on the number of presentations of individual items, not the number of items to be learned (Experiment 3), little mention was made of the transfer results. In the transfer task involving new items, transferability was
dependent on the number of items learned during practice, indicated by the mean response time for the 12 digit trained participants being 263ms, compared to the mean response time of 463ms for the 6 digit trained participants. These results support those of the present study.

Similarly, Schneider and Fisk (1982) reported that the magnitude of transfer in category search differed as a function of the number of items that represented each category during training. When the number of exemplars was increased from four to eight during training, transfer rates increased from 60% to 92%. These results lend further support to the findings of this study. Partial transfer reported by Greig and Speelman (in press) was interpreted to be an indication that skill acquisition was not restricted to the specific task features experienced during training, but neither was it totally generalisable to new situations. They concluded that partial transfer indicated that skill acquisition could be both general and specific. In keeping with this view, and the ACT* theory, in the present study item-general productions would have been developed that could have been applied to any set of values for x and y that were presented. Item-specific productions would also have been developed for each set of values for x and y encountered repeatedly during training. However, item-specific productions could not be used in the transfer task as the values for x and y were different. Therefore, only item-general productions were able to be utilised during the transfer phase. If Schneider and Fisk's (1982) findings apply to these item-general productions, then it would follow that the more exemplars encountered during training that incorporate the application of the item-general production, the greater the transferability of the skill.

According to the ACT* theory, in the training phase of the present study, participants who trained with a small set of x and y stimulus pairs would have been
encouraged to develop highly specific productions for solving the algebraic formula. The composition process would have allowed the proceduralization steps to be collapsed into a one-step process resulting in the correct answer being retrieved for each stimulus pair presented (e.g., if four squared minus eight divided by two is presented for solving, then four is the answer). Participants who trained with a greater number of $x$ and $y$ stimulus pairs would have been encouraged to develop more general productions (e.g., if four squared minus eight divided by two is presented for solving, first square four, then subtract eight and divide result by two, to obtain the answer) as well as the specific productions for solving the algebraic formula. The composition process for these participants would have been a slower process with more practice at performing the intermediate processing steps, before finally developing highly specific productions similar to those of the low variation trained participants. In the training phase, the low variation trained participants would have the advantage, as their specific productions would be faster than the more general productions of the high variation trained participants. However, in the transfer phase, the reverse would be true. Participants who trained with a greater number of $x$ and $y$ stimulus pairs would have the advantage. They would have developed more skill at using the intermediate processing steps that could be implemented in the problem-solving task. The participants who had trained with less $x$ and $y$ stimulus pairs would have less skill in using the intermediate processing steps required to solve the algebraic formula when new $x$ and $y$ stimulus pairs were encountered, as illustrated in Figure 3.

An additional feature of the present study was designed to assess if the components of a skill can be individually useful in the transfer of skill. In the second block of transfer trials, four $x$ and $y$ stimulus pairs were identical to those used in the
training phase, and four x and y stimulus pairs consisted of those whose x values have been encountered during training, and whose y values were encountered only during the transfer phase. If the RT's for the four mixed items in the second block of the transfer task were significantly faster than the RT's for the first block of the transfer task, then it could be assumed that some item-specific production for solving the value of x had been transferred. Although results did not indicate a significant difference between these response times, the means of the response times, as indicated in Table 2, reveal a trend in this direction. There was a 393ms reduction in response time for high variation trained participants, compared to a 210ms increase in the response time for the low variation trained participants, between the first block of transfer items and the mixed items in the second block of the transfer task. Caution is warranted in speculating on this trend, because in the mixed condition of block 42 there were only four trials encountered by each participant, resulting in a mean of only two or three trials in some instances, after deleting incorrect trials. However, these findings would suggest that further investigation of the potential to utilise component knowledge of a skill involved in skill acquisition, as implied by Logan's propositional theory, is warranted.

Implications and Future Directions

It is anticipated that the results of the proposed study will not only add support to the ACT* theory and provide an impetus for further refinement of the instance theory, but that they will lead to more efficient training programs, and as Speelman (in preparation) proposes, a smoother transition from classroom to the workplace. In the present socioeconomic environment, where greater emphasis is being placed on education and training, there is often a conflicting outcome for those
being trained. Training has resulted in highly specific skills, and opportunities to utilise those skills are highly competitive, with the end result that many trainees are forced to look beyond the field of their expertise for implementation. Furthermore, with the accelerated advance in technology, the apparatus and hardware that was used during training is often superceded and in some cases bears little resemblance to that on the shop floor. Based on the findings of the present study, it would appear that more diverse training may lead to more efficient application of acquired skills.

Although the present study indicates that transferability is a function of variability in training with respect to algebraic formula solving skills, further research is needed to enhance the generalisability the results. It is suggested that this hypothesis be tested in other task areas such as lexical decisions, alphabet-arithmetic, and fact recognition. While it is recognised that this study represents only a small sub-domain of cognitive skills, Rickard, Healy, and Bourne (1994) point out that the entire mental arithmetic literature is motivated by the premise that discoveries about mathematical cognition will have implications for general theories of skill acquisition.

Conclusion

Although results of the experiment reported in this paper are consistent with Anderson’s (1982,1992) ACT* theory of skill acquisition. they present several difficulties for the Instance theory as presented by Logan (1988, 1992). Firstly, the instance theory cannot explain the partial transfer observed in the present study. Secondly, the Instance theory cannot explain the improved transfer performance that was obtained by the participants who experienced a greater variation of training.
stimuli when compared to those participants who experienced a lower variation of training stimuli.

With reference to the opening question then, the present study suggests that the mechanic who trained on a greater number of vehicle types would be better able to transfer their skill to the unique, orbital engine technology than would the mechanic who had trained and serviced only Ford and Holden vehicles.
References


Greig, D., & Speelman, C. P. (in press). Is skill acquisition general or specific?


Appendix A

Information and Consent Form

Dear

As part of my research for Bachelor of Arts Honours (Psychology), I am conducting a study looking at factors that limit the transferring of skills from one domain to another. Your help would be greatly appreciated.

This study looks at whether the way in which we acquire specific skills influences our ability to use those skills in a more general setting. You will be asked to solve some simple arithmetic problems on a computer screen and enter your responses into the computer via the mouse. Do not worry if you have never done something like this before, as most participants are the same as you in this respect. The aim is to examine how performing this task is affected by practice. The whole experiment will take less than one hour to complete. You may stop the experiment at any time if you do not wish to continue.

I will not show or discuss your individual results with anyone else. My report of this study will only discuss the average results of all the people who participate in the experiment, and not your individual results.

I will be happy to answer any questions you may have, or if you would like any further information please feel free to contact Doug Brewer or my supervisor Dr Craig Speelman, School of Psychology, Edith Cowen University, Joondalup, WA 6027 ph 94005724.

If you would be prepared to take part in my research, please sign the form below. Thank you for your help!

Yours sincerely,

Expereimenter

Informed Consent

I have read the information above and any questions I have asked have been answered to my satisfaction. I give my consent to participate in this study, realising that I may withdraw at any time. I agree that research data gathered for this study may be published, provided I am not identifiable.

Participant                   Date
Appendix B

On Screen Instructions
First Screen - Introduction

In this experiment you will be required to solve a series of small arithmetic equations. These equations will involve two variables that are to be combined in some way to arrive at a final solution. The equation you are to solve will be the same on each trial. However the values you are to substitute for the variables in the equation will change from trial to trial.

When you have calculated a solution for the equation, you will be asked to decide whether the solution is an odd number or an even number. You will be required to indicate your decision by clicking on the appropriate button on the screen with the mouse.

Click on the button below for some practice at this task.

PRACTICE
Appendix B continued

On Screen Instructions
Second Screen - Practice

\[ \frac{X^2 - Y}{2} = A \]

\[ X = 3 \quad Y = 1 \]

CORRECT

A is ODD

A is EVEN

Note: following box replaced the 'correct' box when the answer was incorrect

INCORRECT - TRY AGAIN
Appendix B continued

On Screen Instructions
Third Screen – More Practice or Start Experiment

If you understand how to do this task, and are happy to go on to do the experiment, please click on the 'experiment' button below. Otherwise, if you would like some more practice, please click on the 'more practice' button below.

Please do not hesitate to ask Doug if you have any questions.

EXPERIMENT MORE PRACTICE
Appendix B continued

On Screen Instructions
For this Screen – Typical Trial Task

\[
\frac{X^2 - Y}{2} = A
\]

\[
X = 5 \quad Y = 9
\]

Note: one of the following boxes appears in the area defined by the dotted box when the answer is registered.

CORRECT

INCORRECT
Appendix B continued

On Screen Instructions
Fifth Screen – Commencement of Trial

Please click on the 'ready' button when you are ready for the next trial

READY
## Appendix C

### Mean Response Times (ms) of Training and Transfer Blocks for Both Low and high Variation Training

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