1-1-2011

Performing New Tasks with Old Skills: Is Prediction Possible?

Craig P. Speelman
Edith Cowan University

John D. Forbes
Edith Cowan University

Kristine Giesen
Edith Cowan University

10.1051/bioconf/20110100085
Speelman, C. P., Forbes, J. D., & Giesen, K. (2011). Performing new tasks with old skills: Is prediction possible?. Paper presented at the International Conference of the European SKILLS Project, Montpellier, France. Available here

BIO Web of Conferences **1**, 00085 (2011)
DOI: 10.1051/bioconf/20110100085

Performing New Tasks with Old Skills: Is Prediction Possible?

Craig P. Speelman* John D. Forbes* Kris Giesen*
(*)Edith Cowan University, Australia
E-mail: c.speelman@ecu.edu.au, john@deltapsychology.com, k.giesen@ecu.edu.au

Abstract

This research evaluated the extent to which power functions can predict performance on a task when performance context has been altered. Since power functions reliably describe performance improvements during practice, an assumption implicit in some theories of skill acquisition and transfer is that transfer performance will continue to improve as an extrapolation of the practice power function. In the training phase of the current experiment, 120 participants practiced solving simple problems from the six times table. In the transfer phase, these same problems were presented again, intermixed with problems from one of six conditions differing in various respects to the target problems. With the exception of two of these six conditions, performance on the target problems was slower than was predicted by training phase power function extrapolations. These findings are discussed in relation to theories of skill acquisition and the role played by a task's conceptual context in transfer performance.

1. Introduction

When time to perform a task is plotted against the amount of practice, a learning curve is typically observed. The shape of this curve is such that improvements in the speed of performance are usually large early in practice, but become progressively smaller as practice continues. Newell and Rosenbloom [5] suggest that power functions provide the best description of such learning curves, and claim that the ubiquity and consistency of power function learning curves mark this phenomenon as a law—known as the power law of learning. One condition for law-like status that was not considered by Newell and Rosenbloom, however, was whether a power function description of a learning curve enables prediction of future performance. Given that performance improvements can be described by a mathematical function, if the task conditions remain consistent, and the motivation of the person performing the task remains constant, then performance should continue to improve according to the function. Therefore, it should be possible to predict future performance by extrapolating the power function that describes past performance.

Explaining the power law of learning is considered a benchmark criterion for evaluating any theory of skill acquisition and transfer [4]. Two theories of skill acquisition, the ACT-R theory [1] and the Instance Theory of Automaticity [4], provide popular accounts of the power law. Both theories also characterise skilled performance as the automatic activation of responses following exposure to particular stimulus conditions. By implication, then, both theories would consider that predictions of the absolute level of performance of a task are possible. That is, if the stimulus conditions and performance goals associated with a task are the same as those encountered during practice, previously acquired skills will be executed in subsequent task performance, and in a way that conforms to the rate of improvement described by the power law. Speelman and Kirsner [8] reported that this is indeed the case. When nothing about a task was changed, a power function that described performance improvements for 288 trials was able to predict the pattern of improvement on a subsequent 288 trials.

The successful prediction of future performance on the basis of a power function description of past performance implies that transfer performance may also be predictable. Given that future performance of a task in an old context can be predicted, then it might be possible to predict future performance in a new context. Certainly the ACT-R and Instance theories imply that if stimulus conditions in a new task context are such that old skills can be executed, then the best prediction of the speed with which those old skills will be executed is determined by extrapolating the power function describing the original improvement of those old skills. In other words, old skills will continue to improve in the context of a new task according to the power function describing the original development of these skills [8].

Speelman and Kirsner [8] tested this prediction. They found that transfer performance did not conform to power law predictions because the predictions consistently underestimated the level of absolute performance. This observation was more closely examined by Speelman and Kirsner [9] in a task involving a series of arithmetic problems. Participants performed the same three calculations during the training and transfer phases, but performed two additional calculations in the transfer phase. Each calculation was constructed in a way that it had to be performed independently, and in a sequence so that old problems were completed before new problems. According to the ACT-R and Instance theories, skills developed during training should have transferred completely to the relevant component of the transfer tasks. Speelman and Kirsner [9] found, however, that reaction time on the old components of the task was slower at the beginning of transfer than at the end of training, indicating that the presence of the novel task components had in some way affected reaction time on the old task components. This disruption was only temporary, though, with performance returning to levels predicted by power function extrapolations, suggesting that the change in task context might prompt an adjustment period.

It is important to note that as well as altering task complexity, Speelman and Kirsner [9] simultaneously altered the visual context of the task by changing the number of calculations between the training and transfer phases. In doing so, they may have altered the conceptual context by prompting participants to conceive the task requirements as being different. 'Conceptual context' is defined as an internal representation of the typical experimental trial that influences cognitive processing and memory retrieval by guiding the contents of working memory [7]. It is therefore possible that any change in the task environment may prompt a change in the conceptual representation of the task, thus affecting task performance.

Since calculations in Speelman and Kirsner's [9] task were added to create the transfer task, a change in the conceptual context may have arisen, and thus been responsible for the observed disruption to transfer performance. It is not possible, however, to determine whether this disruption was induced by the change to the visual appearance of the task or a function of the change in perceived complexity, with participants conceiving of the task as requiring alternative processing rules. Consequently, the current research sought to determine the extent to which the disruption is due to varying the degree of conceptual context while controlling visual context.

The experiment involved presenting a set of target problems common to both the training and transfer phases one at a time, interspersed with a set of distractor problems in the transfer phase. The target problems were presented in an identical manner in both phases of the experiment, and so there were no changes to the visual context of the task from training to transfer. The conceptual context was altered by varying the nature of the distractor problems.

The target problems used in the study involved single-digit multiplication (e.g., 6x2=_) because these problems typically involve simple fact retrieval, and reflect robust and long-standing skills [6]. To facilitate a conceptual change in the task environment, the study employed distractor tasks involving processing rules that varied from subtle to more substantial departures from the target problems. The degree of similarity of the processing rules that underlie solution of the target and distractor problems was varied by selecting distractor conditions that ranged from other arithmetic fact retrieval tasks (or tasks that could be re-cast and then solved by fact retrieval), to algorithmic processing and a combination of algorithmic processing and fact retrieval. There were six distractor conditions: Operand Change (single-digit multiplication items that were unrelated to the target task, e.g., 2x9=_); Operand Reversal (the reversed order of the target items, e.g., 2x6=_); Operation Change (the target items presented in a varied format, e.g., 6x_=12); Symbol Change (the division equivalent to the target items, e.g., 12÷6=_); Double-Digit Addition (which drew on algorithmic processing; e.g., 10+38=_); and Large Multiplication (which involved a combination of memory retrieval and algorithmic processing, e.g., 6x26=_).

It was predicted that if the transfer disruption observed by Speelman and Kirsner [9] is simply due to the overhead of processing rule switching induced by a change in a task's conceptual context, then the disruption should be a function of the degree of departure from the target problem in terms of processing rules. Further, according to the ACT-R [1] and Instance [4] theories, the best prediction of reaction time on the target problems in the transfer phase would simply be an extrapolation of the learning curve that described performance on these problems during the training phase. That is, given that the target problems presented in the transfer phase were identical to those presented in the training phase, performance on the transfer target problems should conform to power function predictions. As such, these theories hold that no transfer disruption should be observed. By examining whether transfer performance will continue to improve as an extrapolation of the practice power function, the present study provides a test of an assumption that is implicit in both the ACT-R and Instance theories, as well as an aspect of the power law of learning.

2. Method

2.1 Participants

The sample consisted of 120 participants, with a mean age of 34.99 years (*SD* = 9.47). There were 38 females (*M* = 33.03 years, *SD* = 8.92) and 82 males (*M* = 35.90 years, *SD* = 9.64). The mean years of schooling for all participants was 13.22 years (*SD* = 3.50). In order to ensure that well-developed skills were being examined, only the data of those participants who attained an accuracy level of at least 80% in the training phase were used in the analysis of the results. Two participants failed to meet the required degree of accuracy, and were replaced.

2.2 Materials

Single-digit items from the Six-Times table were used as the target problems. Multiplication problems containing 0, 1, 5, or ties (e.g., 6 × 6 = __) were excluded as potential confounds, because they involve rule-based solutions rather than memory retrieval, which was the emphasis of the target problems in this study [2]. The remaining six items were used as target problems.

The distractor conditions followed the same exclusionary rules applied to the target problems, giving six distractor problems in each condition. However, in the case of the Double-Digit Addition and Large Multiplication conditions, random double-digit numbers greater than or equal to 13 were used.

2.3 Procedure

Participants were randomly assigned to conditions, and were instructed to complete a series of individually presented arithmetic problems as quickly and accurately as possible. After receiving instructions and 10 practice trials (comprised of problems from the 5x table), participants were presented with the training phase of the experiment. All problems were repeated 12 times and presented in a random order to give a total of 72 training trials. The transfer phase contained the target problems from the training phase in addition to 72 other problems whose nature depended on the experimental condition to which the participant had been allocated. The new and old problems were presented in a random order.

In each trial, participants were initially presented with an individual problem in the centre of a computer screen, and instructed to press the space-bar of the keyboard when they had formed the correct answer. Two possible solutions then appeared on either side of the computer screen; one was a correct response, while the other was a table-related error. Table-related errors are responses that are incorrect for the presented problem, but correct for another problem within the given multiplication table (e.g., a table-related error for 6 × 3 = __ would be 24, which corresponds to the answer for another problem in the 6x table). Presenting table-related errors ensured that participants *generated*, rather than *verified*, a solution [2]. The position of correct answers was counterbalanced across trials between the left and right screen positions.

Participants nominated their response by pressing either the 'z' key to select the option on the left side of the screen, or the '/' key to select the option on the right side of the screen. After making their selection, accuracy feedback was provided by presenting 'Right' or 'Wrong' in the centre of the screen for 500*ms*, after which the next trial commenced automatically. The transfer phase immediately followed the training phase.

3. Results

The data were analysed in blocks of nine trials. This gave a total of eight blocks for the target problems in each phase, as well as eight blocks for distractor problems in the transfer phase, across all six conditions. Mean reaction time (RT) was defined as the elapsed time in milliseconds between initial problem presentation and the left or right button press response. Only correct responses were included in the RT analyses. Accuracy was assessed as the percentage of correct target problems in each block. RT analyses in both phases were performed on the target problems only.

Accuracy on target problem performance was high throughout the experiment (*M* = 97.64%, *SE* = 0.26%). A 6 (condition) × 16 (block) mixed-design ANOVA reported no effect of block or condition, demonstrating that accuracy remained constant in each condition and across all trials, and was not influenced by the introduction of the distractor problems. This finding supports the study's premise that the target problems reflect the retrieval of well-established facts from memory.

There was a high degree of fit between the observed training RTs and power functions derived for each condition, demonstrating that performance during training conformed to predictions based on the power law of learning. Parameters for these functions and measures of goodness of fit (r^2 and root mean squared deviation (rmsd)) are presented in Table 1.

Table 1: *Power Function Fits*

Condition	Power Function	R^2	rmsd (TN)	rmsd (TF)
Operand Change	$y=1541.86+870.55x^{-0.99}$	0.99	20.52	94.23
Operand Reversal	$y=1543.70+921.45x^{-0.80}$	0.98	33.68	92.57
Operation Change	$y=1365.04+1175.16x^{-0.69}$	0.96	54.50	188.91
Symbol Change	$y=1587.28+906.37x^{-0.64}$	0.98	30.58	180.45
Double-Digit Add.	$y=996.25+1911.92x^{-0.47}$	0.98	50.38	417.63
Large Multip.	$y=1744.09+1183.51x^{-1.08}$	0.99	32.94	196.50

To assess the extent to which transfer performance after the distractor problems were introduced could be predicted from training performance, power functions derived from the training phase data were extrapolated a further 8 blocks and compared with observed transfer RTs. Transfer performance was considered to have been predicted on the basis of training performance where extrapolated values passed within the 95% confidence intervals of the transfer RTs (see Figure 1). These figures demonstrate that initial transfer performance was disrupted for the Operation Change, Symbol Change, Large Multiplication, and Double-Digit Addition conditions. However, performance immediately returned to predicted levels in subsequent blocks in the Operation Change and Symbol Change conditions. In the case of the Double-Digit Addition and Large Multiplication conditions, there was a prolonged disruption. While this prolonged disruption was apparent for only the first two blocks of transfer for the Large Multiplication condition, it persisted until the final block of transfer for the Double-Digit Addition condition. The poor fit between predicted and observed RTs in these four conditions provides further evidence of a performance disruption. This is indicated by the high rmsd values (see Table 1) in these conditions, and represents greater deviation from the predicted values than was the case for the training data.

The analyses demonstrate a consistent disruption to predicted initial transfer performance upon the introduction of the distractor problems. In the case of the Operand Change and Operand Reversal conditions, transfer performance was in accordance with training phase predictions for the remainder of the transfer phase after the initial disruption. There are indications from the Double-Digit Addition and Large Multiplication conditions, however, that changes in context that involve more than simply memory retrieval can induce a prolonged disruption to expected performance.

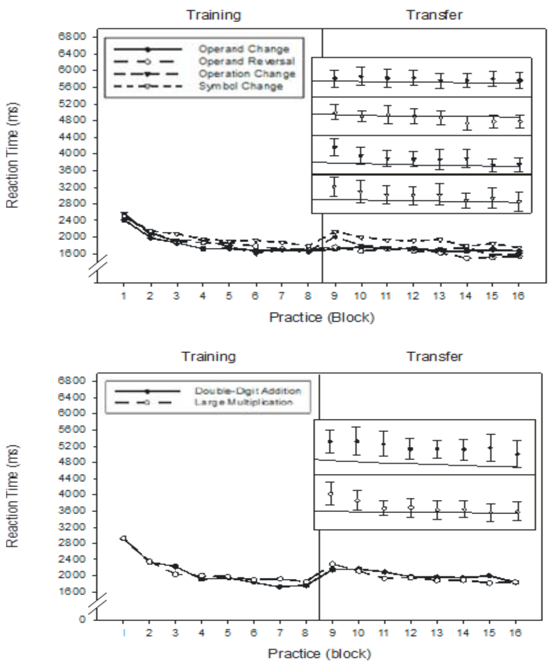

Fig. 1. Comparison of observed (points) and predicted (solid lines in inset panel) RT for target problems. Error bars are 95% confidence limits.

4. Discussion

The present study found an immediate performance disruption similar to that noted by Speelman and Kirsner [9] when the conceptual environment in which the established skills were presented was changed. Consistent with this study's *a priori* predictions, changing the conceptual context of the target problems immediately increased reaction times in the Operation Change, Symbol Change, Double-Digit Addition, and Large Multiplication conditions. The results support the specific findings of Speelman and Kirsner in concluding that skill performance on a task can indeed be disrupted by the presence of a novel task, even when predictions derived from theories such as the ACT-R [1] and Instance [4] theories would indicate that performance should continue in accordance with power functions that describe training performance. Examination of total transfer performance also revealed a prolonged disruption in the Large Multiplication condition, and markedly so in the Double-Digit Addition condition. Thus the present study has clarified the nature of the disruption by demonstrating that the automatic, reflex-like nature of robust skills can apparently be easily disrupted by minor and subtle changes to the context within which these skills are executed (see also [3]).

These findings have significant implications for the ACT-R [1] and Instance [4] theories of skill acquisition. It would appear that the disruption is an observation that should be included in any theoretical framework seeking to describe the entire process of skill acquisition and transfer, particularly since it would be very unlikely that skills can be applied in isolation to any conceptual influences.

5. References

[1] Anderson, J.R. (1993). *Rules of the Mind*. Hillsdale, NJ: Erlbaum.

[2] Campbell, J.I.D. (1987). Network interference and mental multiplication. *Journ of Exp Psych: Learn, Mem, & Cog, 13*, 109-123.

[3] Dishon-Berkovits, M. & Algom, D. (2000). The Stroop effect: It is not the robust phenomenon that you have thought it to be. *Mem & Cog*, *28*, 1437-1449.

[4] Logan, G.D. (1988). Toward an instance theory of automatization. *Psych Rev, 95*, 492-527.

[5] Newell, A., & Rosenbloom, P.S. (1981). Mechanisms of Skill Acquisition and the Law of Practice. In J. R. Anderson (Ed.), *Cognitive Skills and their Acquisition*. Hillsdale, NJ: Erlbaum.

[6] Pesta, B.J., Sanders, R.E., & Murphy, M.D. (1999). A beautiful day in the neighbourhood: What factors determine the generation effect for simple multiplication problems? *Mem & Cog, 27*, 106-115.

[7] Peters, R. Wilson, W. & Powell, A. (1976). Conceptual and associative context effects on speed of word recognition. *Psych Rep*, *39*, 403-407.

[8] Speelman, C.P. & Kirsner, K. (1993). New goals for HCI training: How to mix 'old' and 'new' skills in the trainee. *Int Journ of Hum-Comp Inter*, *5*, 41-69.

[9] Speelman, C.P., & Kirsner, K. (2001). Predicting transfer from training performance. *Acta Psych, 108,* 247-281.