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Testing Instance Models of

Face Repetition Priming

author

Dennis C. Hay

Department of Psychology, Lancaster University

Correspondence concerning this article and requests for reprints should be addressed to Dennis Hay, Department of Psychology, Fylde College, Lancaster University, Bailrigg, Lancaster, England LA1 4YF, telephone (01524) 593831. Electronic mail may be sent to d.hay@lancaster.ac.uk

Abstract

Two experiments examining repetition priming in face recognition are reported. These employed 8 rather than the more usual 2 presentation trials allowing the prediction made by Logan's (1988) instance model of power function speed-up of RT distributions to be examined. Both experiments (the first repeating the same photograph on each trial, the second varying the pose) showed; repetition priming effects for familiar and unfamiliar faces, power function speed-up for both mean and standard deviation of RT and power function speed-up of the quantiles of the RT distributions. It is argued that the findings are consistent with the predictions made by the instance model and provide an explanatory challenge for alternative theoretical approaches.

Testing Instance Models of Face Repetition Priming

Repetition priming describes the phenomenon whereby a previously processed stimulus is recognised more quickly and more accurately on a subsequent presentation. Such effects have been observed in a wide range of face recognition experiments. For example, a speed up of response latency has been observed: when making familiarity judgments to a second and different photograph of a celebrity (Bruce and Valentine, 1985, Ellis, Young, Flude and Hay, 1987); when making occupation judgments to celebrity faces (Young, McWeeny, Hay and Ellis, 1986a); and when naming briefly presented familiar face photographs (Ellis, Young, Flude and Hay, 1987). The contrasting failure to observe repetition priming when making gender decisions (Ellis, Young and Flude, 1990) and expression judgments (Young, McWeeny, Hay and Ellis, 1986b, Ellis, Young and Flude, 1990) led Ellis, Flude, Bruce and Burton (1996) to draw two main conclusions about face repetition priming. First, that priming effects are restricted to those parts of the face processing system which responds to the identity of a face, and second, that there exist two loci at which repetition priming in recognising famous faces operates. The first involves the perceptual recognition of a face as familiar and is in their view domain specific by which they mean that it is restricted to classes of stimuli having a specialised recognition system (Baddeley, 1982). That is, previous exposure to a famous face will prime later presentations of the same photograph or other similar views but will fail to prime the name of that celebrity. The second loci is at the stage of name retrieval and is domain independent. Thus, previously reading aloud the name of a celebrity will prime the subsequent naming a photograph of the face of that celebrity. In a series of experiments Ellis et al. (1996) showed that tasks that involve familiarity or occupational decisions are susceptible to locus 1 priming effects while locus 2 priming is observed in tasks involving face naming.

Ellis et al. also argue that the new data they present are consistent with *structural accounts* of face repetition priming; in particular the Burton, Bruce and Johnston (1990) neural network implementation based on the interactive activation and competition networks of McClelland and Rumelhart (1981). They use the term *structural* to refer to models which embrace the concept of face recognition units (FRU) which are internal representations directly equivalent to the logogens proposed by Morton (1979) to explain how words are recognised. In these accounts repetition priming occurs when the first encounter with a stimulus lowers the activation threshold of the internal representation so requiring less stimulus activation to trigger the representation on a subsequent occasion. Ellis et al. also examine an alternative theoretical account of repetition priming, namely, the episodic or instance based account first offered by Jacoby (1983) and Jacoby and Brooks (1984). They questioned the recognition unit metaphor and demonstrated how priming effects can be entirely explained in terms of instance retrieval. In addition, they suggest that repetition priming results from a process of *perceptual enhancement* where the memory of a previous encounter with stimulus facilitates its recognition. Ellis et al. focus on one particular instance based account, that of Logan (1990), which draws parallels between repetition priming and the development of automaticity in task performance following large amounts of practice. In an attempt to integrate the explanations of these two phenomena Logan highlights three parallels;

(1) that the response time decreases resulting from repetition priming and the development of automaticity are both power functions of the number of exposures.

(2) that both share item specificity. That is, only prior experiences which are similar

to that being processed are retrieved and enhance processing speed,

and

(3) that repetition priming and automaticity both share an associative basis. He proposes that repetition priming is dependent on associations between stimuli and responses or interpretations.

Ellis et al. indicate that their data and those from a number of existing studies create problems for the latter two notions. For example, the findings that the prior reading of a name primed subsequent face naming is inconsistent with Logan's definition of item specificity. The written name and the visual appearance of a face have nothing in common and so presentation of the face for naming should not activate the prior episode of reading the name. Similarly the view of repetition priming as being dependent on the associations between stimuli and interpretations is contradicted by the Ellis et al. (1990) finding that repetition priming does not occur when subjects are asked to decide on the gender of a face or to make expression judgments. Making the second judgment should activate the prior episode that in turn should lead to perceptual enhancement.

The purpose of this article is to rigorously examine the first of the parallels between automaticity and repetition priming suggested by Logan (1990). Perhaps the greatest strength of Logan's instance model is the set of strong predictions made concerning the speed-up in responses to repeated stimuli. In Logan's (1988) theory speed-up results from a processing shift. Initially processing is based upon a set of generic, non-automatic, cognitive procedures (i.e. algorithms) that become replaced by processing involving direct memory access of past instances. The mechanism by which this shift occurs is simply a race between the algorithmic processing and the direct memory mechanism. On any encounter, whichever finishes first generates the response. Initially the algorithm may be more reliable and/or faster but as the number of instances increases the race becomes uneven as the algorithm is competing against an increasing number of instance competitors. Direct memory times speed up as the minimum retrieval time decreases as the number of instances in memory increases. This model makes a number of strong predictions that stem from mathematical simulations of the race between the algorithm and the instances. The first prediction is that performance will speed up with practice and be well fit by a power function of the form,

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

where;

RT is the time required to complete the task,

a is a constant reflecting the asymptotic performance reached,

b, is a constant reflecting the difference between the initial and asymptotic performance,

N is the index of practice (i.e. the number of trials),

and

c is a constant indicating the rate of learning.

This function shape has been shown to apply to a wide range of tasks covering both motor and cognitive learning performance (Newell and Rosenbloom, 1981). The second prediction is that the variability in performance, as measured by the standard deviation of performance over the trials will also decrease with repetition and that this performance is also well fit by a power function. However, what is most surprising is that the power functions describing mean response time performance and the variability in the response time performance as measured by the standard deviation of the response times, are predicted to have equivalent learning rate parameters. This has been formally proven mathematically, substantiated by simulation and supported by empirical data (Logan, 1988). The final prediction is that the entire distribution of response times should decrease as a power function of the number of trials. This can be examined by partitioning the distribution of each trial into quantiles. All quantiles should be well fit by power functions in which the learning rate parameters are equivalent to one another and to those of the overall mean response time and standard deviation functions (Logan, 1992).

Since the majority of face priming tasks have utilised a familiarity decision (i.e. asking subjects to decide if a stimulus face is one known before the experiment) this was thought to be the most appropriate vehicle for investigation. Logan (1988) has shown his model capable of predicting the changes in RT distributions in experiments using word, non-word decisions. This task can be thought of as an analogue of face familiarity tasks only if the same stimulus picture is used on successive trial blocks, and is the paradigm used in experiment 1. However, in everyday face processing we are rarely, if ever, exposed to exactly the same facial stimulus. This begs the question as to what constitutes an instance in the face recognition domain and is the focus of experiment 2. Together, these experiments seek to examine RT performance distributions when the same stimuli are repeated on each trial and to compare this to the more ecologically valid situation in which the pose and expression of individual faces vary from trial to trial.

Experiment 1

Ellis, Flude, Bruce and Burton (1996) differentiate two loci that mediate repetition priming in the recognition of familiar faces. The first involves the perceptual recognition of a face as familiar and is domain specific. That is, deciding a face is familiar is only primed by the previous presentation of some representation of that face.

Experiment 1 employed the simplest possible variant of the tasks used in the previous research examining differences between familiar and unfamiliar face processing (e.g. Bruce and Valentine, 1985; Ellis et al., 1987). This involved making familiarity judgments to the same photograph of famous and unfamiliar faces. The primary aim was to investigate the effects of repetition priming by examining the response time benefits after more than one repetition of the photograph. This study may be considered as extending the basic priming paradigm to allow examination of the benefits to performance through repeated presentation of the same photograph while also providing a direct face processing analogy to Logan's (1988) experiments using words.

Method

Subjects

Thirty psychology students from Lancaster University acted as subjects. All had normal or corrected vision, and had been exposed for a minimum of five years to the British media. They ranged in age from 19 - 32 years and were paid for participating in the experiment.

Stimuli and Materials

Forty-six monochrome images were "frame-grabbed" using the QuickImage system from videotapes of a range of television programs. The images selected ranged from three-quarter right, through full face, to three-quarter left pose and contained a variety of facial expressions. Twenty-three of the images were of celebrities drawn from as wide a range of interests as possible. Each of these was then paired with an image of an unfamiliar face matched on age, post facial hair and spectacle use. The selected images were then standardised. This was done by first cropping the image to maximise the amount of facial information and minimise the amount of background and clothes. Images were then standardised in size (6.5 cm x 4 cm) and equated in brightness and contrast using Adobe Photoshop software and a Macintosh computer.

The stimuli were presented on Macintosh LCII computers with colour monitors. These were viewed at approximately eye level (i.e. the centre of the screen was 35 cm above the height of the desk at which subjects were seated) and situated behind a black screen positioned approximately 60 cm from the subject allowing only the monitor to be viewed. Subjects made their response by pressing one of two buttons on a button box placed on the desk in front of the subject. The buttons were interfaced to the computer and each simulated a single key press of a keyboard key. A filler task was also designed to be used between experimental blocks to ensure subjects had short breaks of around 3 minutes. This required subjects to make word/non-word judgments to lists of letter strings.

Experimental Design

The experimental design and stimulus presentation was handled by the SuperLab application for the Macintosh computers. Subjects first viewed two screens of instructions before completing four practice trials, two of which presented images of celebrities and two of unfamiliar persons. These were followed by a screen listing the instructions for the experiment and informing subjects that they now had an opportunity to ask questions.

There then followed an experimental block consisting of six lead in trials (the data from which did not enter into the analyses) and forty experimental trials. Half of all trials presented images of celebrities and half of unfamiliar faces. Both the lead in trials and the experimental trials were randomised before each presentation and subjects viewed the trail block eight times. Between each experimental block subjects were required to complete one of the pages of the filler task word booklet.

The background colour of the screen for each of the lead in and experimental trials was a pale blue upon which the word "ready" appeared in red letters approximately 1.5 cm tall. This was displayed for 2000 ms in the centre of the screen and was replaced after a 500 ms interstimulus interval (ISI) with a central red dot. This was presented for 500 ms and was again followed by a 500 ms ISI followed by a stimulus face presented centrally for 2500 ms. Subjects were then required to respond by pressing one of the two buttons. A further 1000 ms ISI preceded the presentation of the "ready" signal that indicated the start of the next trial sequence. After each block of trials instructions appeared instructing the subjects to fill in one of the pages of the word booklet.

<u>Procedure</u>

Subjects sat at a desk facing the monitor and were instructed to place the index finger of each hand on the two buttons and to locate the button box in a comfortable position. They were then asked to read the instructions presented on the screen. These indicated that the experiment was designed to investigate how familiar and unfamiliar faces are processed and that a series of faces was to be presented. Subjects had to decide if a particular face was one of a famous celebrity or of someone unknown at the start of the experiment and to indicate their decisions by pressing the appropriate button. They were asked to make decisions as quickly and as accurately as possible and to complete the practice trials. At the end of these the experimenter indicated what the correct responses were and asked if subjects had any problems or questions. The experimenter then verbally repeated the instructions to be as fast and as accurate as possible before allowing subjects to start the experiment proper. Each subject then completed eight consecutive experimental blocks interspersed by them completing one page of the filler task booklet.

For half the subjects pressing the right button was used to indicate the image was of a celebrity and for half the mapping was reversed.

Results

The analyses were of two forms. First analyses of variance (ANOVAs) were conducted on the response time (RT) data as this is the primary method used in previous face priming research to examine differences between familiar and unfamiliar face processing. Secondly, power curve parameters were fitted to the data as a means of examining the validity of the instance-based model and to allow comparisons between the forms of analysis presented in this study and the series of studies following Logan (1988).

ANOVAs of the Response Time Data

For each subject the RT's from the 20 famous and the 20 unfamiliar faces and the errors were collected. The average error rate for famous faces was 1.99% and for unfamiliar faces 3.19%. Since so few error occurred no formal analyses were conducted. Trials on which errors were made were removed and the mean correct RT and the standard deviation for each subject for each trial block for both stimulus classes calculated. This generated a 2 x 8 within design (type of face x experimental block) and subsequent ANOVA revealed both main effects to be significant (see table I). Famous faces were recognised significantly faster than unfamiliar faces $\underline{F}$ (1,29) = 57.15, $\underline{MSE}$ = 127555.07, $p < 0.001$ and performance over the experimental blocks showed the expected practice curve decrease $\underline{F}$ (7,203) = 62.68, $\underline{MSE}$ = 3284.51, $p < 0.001$.

In addition, the interaction between type of face and experimental block (see Figure 1) was also significant. This occurred as a result of the RT's to familiar faces taking fewer trials to drop from their initial position to their asymptotic level, that is, they show a much steeper rate of decrease than unfamiliar faces, $\underline{F}$ (7,203) = 11.78, $\underline{MSE}$ = 1248.77, $p < 0.001$. Exploration of this interaction involved conducting a number of comparisons. As most of repetition priming experiments using faces have involved only one repetition, the first analysis examined performance on the initial two trials. This indicated that the overall type of face x block interaction was not due to a differential reduction in RT for familiar and unfamiliar faces on the first two trials, $\underline{F}$ (1,29), = 0.007, $\underline{MSE}$ = 0.11, $p = 0.993$. Similar analyses on subsequent trial pairs indicated that the reduction in mean RT on trials two and three for unfamiliar faces was 50.7 ms which was significantly greater than the drop in RT for familiar faces which was 36.4 ms $\underline{F}$ (1,29) = 5.21, $\underline{MSE}$ = 3842.10, $p < 0.05$. As will be seen this is consistent with the power function fits which indicate unfamiliar faces continuing to improve over a number of trails while familiar faces approach asymptotic performance much more quickly.

A similar overall analysis was conducted on the standard deviations calculated from the RT data. For each subject the standard deviation of the scores for famous and unfamiliar faces in each of the experimental blocks was calculated producing a 2 x 8 within design (type of face x experimental block). Subsequent ANOVA revealed both main effects to be significant (see table I). Standard deviations for famous faces were significantly lower than those for unfamiliar faces, $\underline{F}$ $(1,29) = 10.98$, $\underline{MSE} = 2370.33$, $p < 0.0025$ and performance over the experimental blocks mirrored the practice curve decrease seen for the mean RT's, $\underline{F}$ $(7,203) = 9.212$, $\underline{MSE} = 1528.74$, $p < 0.0001$. The interaction, although of a similar shape to that observed for the mean RT data (see Figure 1) did not reach significance.

Power Curve Parameter Estimation

The instance theory detailed by Logan (1988, 1992) makes three strong predictions. First, that data from conditions in which subjects make the same decision to the same stimuli in repeating blocks of trials are well fit by power functions of the form;

$$\text{RT measure} = a + b(\text{Trial Block})^{-c}$$

Secondly, the mean and standard deviation power functions of the data from each type of face should be well fit by power functions and have the same c parameter (Logan, 1988). Thirdly, the quantiles of the RT data distributions should also be well fit by power functions and have common exponents.

The analysis strategy used to examine these predictions involved fitting power functions to various RT summaries. A number of different algorithms were employed including using the STEPIT algorithm (Chandler, 1965) used by Logan (1998, 1992), the Newton, the Quasi-Newton, the Steepest Descent algorithm (Raner, 1994) and the Levenberg-Marquard algorithm (Press, Flannery, Teukolosky and Vetterling, 1992). These all produced similar solutions. The prediction of common rate exponents was examined by constraining the c parameter to be equal across functions while allowing the other parameters to vary freely, and to select the common exponent that minimised the error fit statistics for the functions under consideration. The constrained fits could then be compared to the unconstrained fits as a means of examining the validity of the instance theory predictions (Logan, 1988). Finally, the comparison between a constrained fit and the corresponding unconstrained fit is equivalent to the situation in which an additional independent variable is added to a regression equation. In such circumstances it is possible to test whether there has been a significant change in explained variance (R^2) by evaluating the corresponding t-statistic.

The data for examining the predictions relating to the distribution quantiles were prepared for this analysis by combining the individual subject's RT's to produce a group RT distribution calculated over five quantiles. Thus for each subject 5 quantiles (i.e. the quintiles which are the value of the 10th, 30th, 70th and 90th percentiles) were calculated and averaged over subjects (see Ratcliff (1979) for a full discussion of group RT distributions and quantile calculations). For completeness the summary statistics for each block (collapsed over subject and stimulus) were also calculated and yielded similar power functions and so only the quintile data are presented.

Following this strategy, power functions were fit to the overall mean RT and standard deviation data (see Figure 1) and the estimated parameters and the measures of goodness of fit are presented in Table 2. These clearly show that the data are well fit by power functions (alternative functions were also explored but in all cases power functions produced superior fits) and that the prediction generated by Logan's (1988) instance theory of the mean and the standard deviation functions exhibiting common exponents (c parameters) is supported for both famous and unfamiliar faces. These show different forms of processing with the famous face functions showing a rate of decline more than twice that shown for unfamiliar faces.

Moreover, when the exponents for mean and standard deviation functions were constrained to be the equal and to minimise the error measures for each type of face, the fits were only marginally poorer than when the parameters were unconstrained. This conclusion is supported by the analysis of the changes in the values of R^2 which were found to be non-significant in all cases (see Table 2).

The power functions were also fit to the quantile data from the famous and the unfamiliar face data (see Figure 2). The estimated parameters and the goodness of fit measures to the quantile data from both famous and unfamiliar faces is presented in Table 3. As before, power functions fit the data from both famous and unfamiliar faces extremely well with the exponents for the different quantile functions being similar within each type of face. The c parameters of the individual quantile functions were also constrained to be equal to the value used to constrain the overall data for famous and unfamiliar faces and again the decrease in R^2 was non-significant in all cases (see Table 3).

Discussion

The ANOVA and curve fitting results produce a consistent picture which confirms that both familiar and unfamiliar faces exhibit RT performance curves that are well fit by power functions. Not only are the mean and standard deviation data well fit by power functions but there is also strong support for the prediction that these and the quintile data have similar power function exponents. These data are in line with the predictions made by Logan's (1988) instance model. In contrast, current models of face processing based around FRU's, such as that of Bruce and Young (1986) or the neural net implementation based on McClelland and Rumelhart's (1981) interactive activation model produced by Burton et al.

(1990) are unable to make quantitative RT predictions of this detail.

These models have particular difficulty in explaining the speed up in the processing of unfamiliar faces. Since these have no FRU they should not exhibit similar patterns of RT speed-up as shown by familiar faces and this finding clearly highlights one of the key gaps in structural model accounts of face processing, namely, the processes by which FRU's are formed and how these interact with the processing of unfamiliar faces.

However, although the data from the current experiment indicate that familiar and unfamiliar faces have similarly shaped RT functions these are not identical. The major differences between these functions lies in the first half of the RT curves. Familiar faces are initially processed more quickly but have an asymptote similar to that of unfamiliar faces. In fact, constraining the asymptote to be the same for familiar and unfamiliar faces makes little difference to the power function fits. However, familiar faces do exhibit a steeper learning rate (i.e., a larger c parameter). Such a pattern is consistent with the findings from studies using similar paradigms with familiar and unfamiliar letter strings (Logan, 1988; Logan, 1990). This pattern indicates that repeated exposure is sufficient, in the long run, for unfamiliar faces to behave like familiar faces and would argue against the notion of a processing change that is dependent on the formation of a new structure such as an FRU. The initial differences in the shapes of the RT functions could be explained by the fact that familiar faces already have existing instances to assist processing while unfamiliar faces must create new instances and have a minimal number early in the experiment.

What complicates this simple explanation is that the word studies of Logan and the present study used exactly the same stimuli on each trial. While this is a legitimate tactic in word recognition it is far from ecologically valid in the face processing domain where seeing exactly the same stimulus twice is the exception. Changes in pose, lighting, expression, hairstyle and age mean that a range of discrepancies are possible between two exposures. Would such different stimuli be considered instances? If not the RT functions observed in this experiment would not be repeated and the usefulness of Logan's instance model would be severely limited in its application.

Experiment 2

As has been frequently pointed out (e.g., Hay and Young, 1982; Hay, young and Ellis, 1986) recognising the same photograph may not employ exactly the same processes used when recognising individuals in real life situations. In these the stimulus involved is unlikely ever to be exactly the same as one encountered previously. In fact, face recognition may best be considered a visual categorisation task in which a new stimulus (e.g., a new exposure to Madonna) is assigned to the visual category Madonna's face.

Thus, in an attempt to be more ecologically valid, experiment 2 employed different poses in each of the eight trial blocks.

Method

Subjects

Thirty psychology students from Lancaster University acted as subjects. All had normal or corrected vision, and had been exposed for a minimum of five years to the British media. They ranges in age from 19 - 30 years and were paid for participating in the experiment.

Stimuli and Materials

Video clips of a range of celebrities were collected from TV productions. Each was around 2 minutes duration and contained a range of head movements and expression changes. From these twenty-three celebrities were drawn to sample as wide a range of interests as possible. Similarly, clips of unfamiliar faces were collected from German and Dutch TV programs and films in an attempt to equate the quality and range of faces. Twenty-three of these were selected to match the chosen celebrities on gender, age, facial hair and spectacle use.

These video clips yielded eight monochrome images that were "frame-grabbed" using the QuickImage system. The images selected for each individual ranged from three-quarter right, through full face, to three-quarter left pose and contained a variety of facial expressions. The selected images were then standardised by first cropping the image to maximise the amount of facial information while minimising the amount of background and clothes. Images were then standardised in size (6.5 cm x 4 cm) and equated in brightness and contrast using Adobe Photoshop software on a Macintosh computer.

Procedure

All other aspects of the procedure were the same as used in experiment 1.

Results

The initial analyses took the same form as those detailed in experiment 1.

ANOVA's of the Response Time Data

For each subject the RT's from the 20 famous and the 20 unfamiliar faces and the errors were collected. The error rate for famous faces was found to be 2.35% and for unfamiliar faces 4.13%. Trials on which an error was made were removed and the mean correct RT and the standard deviation for each subject for each trial block for both stimulus classes was calculated.

This yielded mean RT data in a 2 x 8 within design (type of face x experimental block). Subsequent ANOVA revealed both main effects to be significant (see table 4). Famous faces were recognised significantly faster than unfamiliar faces, F (1,29) = 79.74, MSE = 11587.50, $p < 0.0001$ and performance over the experimental blocks showed the usual practice curve decrease, F (7,203) = 76.44, MSE = 2237.46, $p < 0.0001$.

In addition the interaction between type of face and experimental block (see Figure 3) was also significant. As in experiment 1 this showed a much steeper rate of decrease for famous faces than unfamiliar faces F (7,203) = 4.42, MSE = 868.57, $p < 0.0001$. A similar analysis was conducted on the standard deviation data. For each subject the standard deviation of the scores for famous and unfamiliar faces in each of the experimental blocks was calculated producing a 2 x 8 within design (type of face x experimental block). Subsequent ANOVA revealed both main effects to be significant (see table 4). Standard deviations for famous faces were significantly lower than those for unfamiliar faces, F (1,29) = 7.52, MSE =

855.049, $p < 0.05$ and performance over the experimental blocks mirrored the practice curve decrease seen for the mean RT's ($F(7,203) = 6.26$, MSE = 424.764, $p < 0.001$). The interaction, although of a similar shape to that observed for the Mean RT (see Figure 3) did not reach significance.

Power Curve Parameter Estimation

As before power functions produced better fits than other similarly shaped function and so only the power fit data are presented. The data were prepared for this analysis by combining the individual subject's RT's to produce a group RT distribution calculated over five quantiles.

Power functions were fit to the overall mean RT and standard deviation data (see Figure 3) and the estimated parameters and the measures of goodness of fit are presented in Table 4. These clearly show that the data are well fit by power functions and that the prediction generated by Logan's (1988) instance theory of the mean and the standard deviation functions exhibiting common exponents (c parameters) is supported separately for both famous and unfamiliar faces. These show different forms of processing with the famous face functions showing a rate of decline more than twice that shown for unfamiliar faces. Moreover, when the exponents for means and standard deviations were constrained to be the equal and to minimise the error measure for each type of face, the marginal decrease in R^2 between unconstrained and constrained fits was found to be nonsignificant; all values of t being less than one (see table 5).

Power functions were also fit to the quantile data from famous and unfamiliar face data (see Figure 4). The estimated parameters and the goodness of fit measures to the quantile data from both famous and unfamiliar faces is presented in Table 3. As before, power functions fit the data from both famous and unfamiliar faces extremely well with the exponents for the different quantile functions being similar within each type for face. The c parameter of the individual quantile functions was again constrained to be equal to that used when constraining the overall data for famous and unfamiliar faces (see Table 5). As before the constrained functions produce parameters and fits that are very similar to those generated by the unconstrained fits. In all cases the change in R^2 between constrained and unconstrained fits was found not to differ significantly (see table 6).

Comparisons of Experiments 1 and 2

The analyses so far have indicated a good fit between the predictions made by Logan's instance model and the current data. Additional analyses were conducted to further determine if changes in response performance were dependent on a move from identical stimuli presented on each trial to stimuli that changed in pose and expression from trial to trial. Of particular importance for the notion of what constitutes an instance are the interactions, for each type of face, between type of pose (i.e., fixed pose in experiment 1 and varied post in experiment 2) and performance over trials. Planned comparisons revealed that these interactions were non-significant for familiar faces, $\underline{F}\ (7,406) = 0.59$, $\underline{MSE} = 1373.15$, $p > 0.05$ and for unfamiliar faces $\underline{F}\ (7,406) = 1.44$, $\underline{MSE} = 244.50$, $p > 0.05$. Similarly no significant differences involving pose were found in analyses of the standard deviation data. The similarity between the power curves across experiments can be seen by comparing the data plotted in figures 1 and 3 and the curve fits displayed in tables 2 and 5. To assess the consistency of this pattern power curves were fitted to each subject's familiar and unfamiliar face data in both experiment one and experiment two. The increased noise inherent in the individual data meant that it was impossible to fit power functions in all cases that had positive values for the asymptotic (i.e. the *a*) parameter. Negative values are psychologically impossible implying that performance speeds to the extent of producing negative RT's. This pattern was observed in only 13 cases (nine from experiment 1 and four from experiment 2) and the data from these subjects were removed from the following analyses. Separate 2 x 2 ANOVAs (type of pose x type of face) were conducted for each of the three estimated parameters. Investigation of the asymptotic parameters (the *a* parameter) revealed no significant differences between the types of pose, the type of familiar face nor any interaction between these factors. For the *b* parameter - the measure of the difference between initial performance and asymptotic performance - the analysis indicated only a significant main effect of familiarity with the *b* parameter being significantly less for familiar faces (194 ms) than that for unfamiliar faces (317 ms), $\underline{F}$ (1,45) = 22.05, $\underline{MSE}$ = 16115.1, $p < 0.001$. Similarly, the analysis of the *c* parameter - the index of the rate of learning - also only revealed a significant effect of familiarity, $\underline{F}$ (1,45) = 5.56, $\underline{MSE}$ = 54.18, $p < 0.05$, confirming that this was significantly greater for familiar (-3.82) than for unfamiliar (-0.95) faces.

Discussion

As before the data are well fit by power functions and both the standard deviation and the mean RT curves for familiar and unfamiliar faces exhibit functions with learning indices similar to those observed in experiment one. With the quantile data also being well fit by power curves with similar indices, the data again offer strong support for the predictions generated by Logan's instance model. In this experiment changing the pose from trial-to-trial produced no observable differences from the functions and parameters observed in the previous experiment confirming the flexibility of Logan's model and demonstrating that it is not restricted to situations in which the stimulus-response instance is identical on consecutive trials.

As before familiar faces yielded functions which differed from those obtained for unfamiliar faces. These differences were restricted to the parameters measuring early RT performance and not the level of the asymptote. The lower *b* parameter is a result of the familiar face function having a lower performance on trial one relative to the same asymptotic level which the c parameter indicated is reached in fewer trials for familiar faces than for unfamiliar faces.

General Discussion

The main objective of this paper was to rigorously examine the predicted power function speed-up of RT when applied to face repetition priming. The findings presented here appear to offer clear support for the predictions made by Logan's instance model. Specifically, these are;

a) that speed-up in RT performance takes the form of a power function. This was observed in both experiments for both familiar and unfamiliar faces.

b) that learning rate parameter for the power functions fitted to the mean RT and the standard deviation of the RT's in each trial block are the same. The constrained fits support this position for RT's to both familiar and unfamiliar faces.

and,

c) that different quantiles of the RT distributions also share the same learning rate parameter. Again the evidence from both experiments support this prediction.

These data pose a number of significant problems for structural accounts of face processing. Perhaps the most obvious is that these can offer no predictions as to what RT performance in repetition priming tasks will be. Face recognition units (FRU's), like logogens, are black box constructs containing both the internal representation and the process by which this is matched with the incoming visual stimulus. The lack of specification makes these useful *descriptive* devices but mean they have a consequential low predictive power. The lowering of a threshold is seen as correlating with a reduction in RT but it remains to be seen how this mechanism can be modified to account for the power function speed-up in the various measures of RT performance demonstrated here. Structural accounts are also limited in that they deal only with preformed units and suggest that unfamiliar faces, having no associated unit, should show no RT performance decrease with repetition. As in the Bentin and Moscovitch (1988) study the current data revealed "priming-like" behaviour with unfamiliar faces. This was true even in the situation in which different poses of the same unfamiliar face were seen on different trials. Thus, the contention that face repetition priming effects only occur within the part of the system handling familiar face recognition (Ellis et al., 1990; Ellis et al. 1996) finds little support and is further weakened by the demonstration by Hay (in press) of repetition priming effects in an expression judgment task. This reveals similar levels of "expression" priming for familiar and unfamiliar faces. More interestingly, Logan's instance theory was used to predict the conditions under which such effects would be obtained with the results matching these predictions.

Some integration of the FRU and instance positions may be possible. For example, the Burton et al. (1990) models is based on the interactive activation network suggested by McClelland and Rumelhart (1981). More recent and comprehensive versions of this seek to explain the development of what appear to be abstractive word and concept units as resulting from the storage of all instances of the word or concept (McClelland and Rumelhart, 1985). Models such as these respond strongly to prototypical patterns while also responding strongly to recent instances in the training set.

The data from the two experiments presented here present different problems for Logan's instance model. The consistent finding is that although familiar and unfamiliar faces both exhibit power function speed-up the shape of the functions differ. Familiar faces are initially processed faster and have a greater learning rate parameter. The initial fast processing of familiar faces is a common finding in face decision tasks (Bruce and Valentine, 1985; Hay, Young and Ellis, 1986; Young, McWeeny, Hay and Ellis 1986a; Ellis, Young, Flude and Hay, 1987). Both structural and instance theories can explain this phenomenon. The FRU model suggests that since unfamiliar faces have not previously been seen and the task requires a judgment of familiarity, deciding a face is unfamiliar is the default option if a face is not considered familiar. In a Logan instance model this is also a possibility resulting from different algorithmic processes for familiar and unfamiliar faces.

However, the difference in the learning rates for familiar and unfamiliar faces could also be interpreted as evidence of a qualitatively different underlying processing mechanism and the instance model offers two possibilities to explain this differential speed-up. The first relates to the simplifying assumptions made in order to make the theory easy to analyse and simulate. Namely, that the algorithmic processing remains unchanged with practice. As Logan (1988) points out this is unlikely to be true in general and in his personal communication in response to Kirsner and Speelman (1996), indicated how this model can be modified to support practice effects and the additive relationship they observed between repetition priming and practice. Another possible explanation exists that relates to question of what constitutes an instance and which instances enters the race. For familiar faces it is possible that a number of pre-experimental instances already exist. It could be that after the first trial rather than only one "familiar face decision" instance being available a number are sufficiently useful and enter the race. If the system is flexible enough the number of *appropriate* instances might increase in subsequent trials until all available "familiar face decision" instances are employed. This implies that the familiar faces performance is a function not of the number of experimental trials but of the number of instances in the race on any experimental trial. Unfortunately a host of possible instance values which increase over trials exist all of which can be fit by power functions. However, it is interesting to note that one of those which produces a particularly good fit has power function parameters very similar to those found here for unfamiliar faces. This opens up the possibility that a single process underlies the repetition priming effects demonstrated here for both familiar and unfamiliar faces.

Although it is possible to adapt the basic instance model to account for the observed differences in familiar and unfamiliar function shape, there is evidence from both psychological and computational approaches to the problem of how faces are recognised which is directly relevant to this discussion. These concentrate exclusively on how suitable internal representations are derived from differing visual exemplars. The psychological studies in which the rotational angle of the head is varied between initial presentation and recognition (usually some combination of frontal three-quarter and profile) support the broad conclusion that recognition performance varies with face familiarity. Familiar faces tend to be insensitive to rotational transformation while unfamiliar face recognition performance tends to decrease with rotational transformation (Bruce, 1982; Krouse, 1981; Bruce, Valentine and

Baddeley, 1987). This performance change is frequently interpreted as indicative of a qualitative difference in the nature of the internal representations formed for familiar and unfamiliar faces (Valentin, Abdi and Edelman, 1997) and such explanations could be employed to explain the differing power functions obtained here. The fact that the three-quarter view of unfamiliar faces leads to better recognition performance than other views is interpreted as suggestive of a system with multiple view dependent representations (Valentin et al.). There seem to be two ways of implementing such multiple view systems; those which store sufficient instances to allow any novel view to be close to one of the image set which is a variant of the Logan model in which all instances are stored, or what Moses, Ullman and Edelman (1996) call the interdependent approach. In this type of system only a small number of specific orientations are stored and used to extract the three-dimensional information (e.g., Edelman, 1995; Bulthoff, Edelman and Tarr, 1995). In their simulations Valentin, Abdi and Edelman (1997) demonstrated that a system which stored only two views (frontal and profile) was sufficient to accurately identify 09% of multiple pose face views. Such a system has a degree of neurophysiological validity as evidence from single cell recording of activity in the temporal cortex of monkeys presented with faces found cells with a statistical preference for these views (Perret, Heitanen, Oram and Benson, 1992). Unfortunately, these systems currently provide only accuracy data while the Logan instance models provides only response time predictions. It remains to be seen if systems based on the interdependent approach can reproduce repetition priming phenomena in genera and RT power functions of the form reported here. Particularly important is the power function speed-up associated with unfamiliar faces which relates to recognition performance while new internal representation are being created and developed. It is for this incremental process that the Logan model is especially suited.

However, it is unlikely that the link between the power function speed-up of RT and Logan's instance theory is unique. Van Zandt and Ratcliff (1995) investigated a range of statistical architectures which mimic existing cognitive models. They show that a mixture of gamma functions can produce RT data with the characteristics predicted by Logan's model. The authors do add, however, that there is no theoretical basis behind their use of gamma functions; they merely use these as a demonstration that alternatives exist. This is in contrast to Logan's instance theory which is based on a number of explicit assumptions which predict distributional changes of the type observed in the current experiments.

There may also be a problem with the mathematical underpinnings of the instance theory as indicated by the interchange between Colonius (1995) and Logan (1995). Although both are in agreement that the development of automaticity is well characterised by a race between instances, there appears to be a problem concerning the conditions under which it justified to choose the Weibull distribution as the underlying parent distribution for the minima of the RT's. What emerges is that the argument used by Logan for choosing this function has at least one error and Colonius suggests an alternative argument to support the choice of the Weibull distribution based on Huang's (1989) theorem. This proves that the sequence of *means* of minima uniquely determines the *distribution* of the minima. For example, if the mean RT's conform to a power function, then the whole distribution of RT's are constrained to be this shape and distributional indices such as the standard deviations and the quantiles will also exhibit this shape. Thus this proof of the instance theory implies that the means constrain the shape of the distribution which is neither the general case (Townsend, 1990) nor a property of alternative psychological theories (Morton, 1979; Compton and Logan, 1991).

In his reply to Colonius, Logan (1995) suggests that before power function speed-up in RT distributions is viewed as a corner stone of the instance theory, he would like to see more evidence of its robustness and generality. The data presented here provide conformation that the RT distributions from another psychological domain (i.e. face repetition priming) exhibit power function speed-up. The challenge facing proponents of alternative approaches is clear. Can these be modified and/or better specified to encompass these results or is the instance theory the only existing viable model?

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Table 1

The ANOVA based mean RT's (msec) and mean standard deviations from Experiment 1 for each of the classes of face and for each experimental trial block

Type of Face	**RT**	**S.D.**
Famous	595	104.1
Unfamiliar	673	116.1

Block	**RT**	**S.D.**
1	761	137.1
2	671	127.5
3	640	108
4	615	100.8
5	602	98.9
6	601	104.9
7	589	96
8	591	96.5

Table 2

Parameter estimates from unconstrained and constrained fits of power functions (RT = a + b (Block) $^{-c}$) to means and standard deviations of response times to the famous and unfamiliar faces used in Experiment 1. The significance of the decrease in R^2 due to constraining the c-parameter is given by the value of t which was non-significant in all cases.

		Unconstrained	**Constrained**	**t**
	a	557	551	
Famous Face	b	144	148	
Mean RT	c	-1.34	**-1.18**	
	R^2	0.982	0.979	0.91 (n.s.)
	rmsd	7.72	7.88	
	a	77	83	
Famous Face	b	59	54	
S.D. RT	c	-0.9	**-1.18**	
	R^2	0.905	0.903	0.32 (n.s.)
	rmsd	6.4	6.48	
	a	500	483	
Unfamiliar Face	b	324	340	
Mean RT	c	-0.52	**-0.48**	
	R^2	0.991	0.991	0.00 (n.s)
	rmsd	8.26	8.34	
	a	72	79	
Unfamiliar Face	b	70	64	
S.D. RT	c	-0.41	**-0.48**	
	R^2	0.842	0.839	0.31 (n.s)
	rmsd	6.93	7.00	

Table 3

Parameter estimates from unconstrained and constrained fits of power functions (RT = a + b (Block) $^{-c}$) to the 5 quantiles of the response time distributions of the famous and the unfamiliar faces used in Experiment 1. The significance of the decrease in R^2 due to constraining the c-parameter is given by the value of t which was non-significant in all cases.

Unconstrained Fits

Type of Face	**Quantile**	**a**	**b**	**c**	**R^2**	**t**	**rmsd**
	1	671	236	-1.05	0.954		18.28
	2	581	163	-1.41	0.986		7.28
Famous	3	545	133	-1.63	0.986		6.19
	4	510	108	-1.38	0.990		4.15
	5	468	86	-1.37	0.958		6.79
	1	592	445	-0.45	0.971		18.48
	2	519	357	-0.53	0.994		7.32
Unfamiliar	3	468	329	-0.49	0.991		7.78
	4	475	267	-0.60	0.991		7.74
	5	438	230	-0.61	0.985		8.10

Constrained Fits

Type of Face	**Quantile**	**a**	**b**	**c**	**R^2**	**t**	**rmsd**
	1	680	229	*-1.18*	0.953	0.33	18.47
	2	572	169	*-1.18*	0.984	0.85	7.91
Famous	3	534	141	*-1.18*	0.977	1.79	7.86
	4	504	112	*-1.18*	0.988	1.00	4.53
	5	464	89	*-1.18*	0.956	0.49	6.92
	1	610	427	*-0.48*	0.971	0.00	18.51
	2	498	377	*-0.48*	0.994	0.00	7.46
Unfamiliar	3	463	334	*-0.48*	0.991	0.00	7.78
	4	439	301	*-0.48*	0.988	1.00	8.21
	5	404	261	*-0.48*	0.984	0.58	8.48

Table 4

The ANOVA based mean RT's (msec) and mean standard deviations from Experiment 2 for each of the classes of face and for each experimental trial block

Type of Face	**RT**	**S.D.**
Famous	592	105.1
Unfamiliar	680	112.4

Block	**RT**	**S.D.**
1	754	135.4
2	665	111.7
3	643	113.9
4	622	107.8
5	611	98.3
6	605	107.2
7	595	99.5
8	595	96.4

Table 5

Parameter estimates from unconstrained and constrained fits of power functions (RT = a + b (Block) $^{-c}$) to means and standard deviations of response times to the famous and unfamiliar faces used in Experiment 2. The significance of the decrease in R^2 due to constraining the c-parameter is given by the value of t which was non-significant in all cases.

		Unconstrained	**Constrained**	**t**
	a	551	555	
Famous Face	b	154	151	
Mean RT	c	-1.20	**-1.31**	
	R^2	0.987	0.986	0.61 (n.s.)
	rmsd	6.43	6.58	
	a	95	93	
Famous Face	b	40	42	
S.D. RT	c	-1.56	**-1.31**	
	R^2	0.887	0.885	0.30 (n.s.)
	rmsd	5.53	5.60	
	a	560	556	
Unfamiliar Face	b	262	265	
Mean RT	c	-0.61	**-0.60**	
	R^2	0.994	0.994	0.00 (n.s)
	rmsd	5.76	5.76	
	a	85	85	
Unfamiliar Face	b	53	53	
S.D. RT	c	-0.60	**-0.60**	
	R^2	0.878	0.878	0.00 (n.s)
	rmsd	5.81	5.81	

Table 6

Parameter estimates from unconstrained and constrained fits of power functions (RT = a + b (Block) $^{-c}$) to the 5 quantiles of the response time distributions of the famous and the unfamiliar faces used in Experiment 2. The significance of the decrease in R^2 due to constraining the c-parameter is given by the value of t which was non-significant in all cases.

Unconstrained Fits

Type of Face	**Quantile**	**a**	**b**	**c**	**R^2**	**t**	**rmsd**
Famous	1	702	204	-1.36	0.965		14.51
	2	576	186	-1.18	0.990		6.95
	3	526	152	-1.07	0.983		7.09
	4	495	129	-1.15	0.986		5.62
	5	454	101	-1.21	0.988		4.17
Unfamiliar	1	594	428	-0.4	0.979		14.11
	2	590	286	-0.66	0.991		8.06
	3	565	239	-0.75	0.998		3.00
	4	529	213	-0.71	0.998		2.62
	5	475	192	-0.61	0.996		3.50

Constrained Fits

Type of Face	**Quantile**	**a**	**b**	**c**	**R^2**	**t**	**rmsd**
Famous	1	700	205	*-1.31*	0.965	0.00	14.54
	2	582	182	*-1.31*	0.989	0.71	7.22
	3	536	144	*-1.31*	0.980	0.94	7.72
	4	501	125	*-1.31*	0.984	0.85	5.88
	5	456	100	*-1.31*	0.987	0.65	4.25
Unfamiliar	1	690	338	*-0.6*	0.976	0.85	15.14
	2	575	300	*-0.6*	0.991	0.00	8.20
	3	536	264	*-0.6*	0.997	1.58	4.34
	4	510	230	*-0.6*	0.997	1.58	3.30
	5	474	193	*-0.6*	0.996	0.00	3.51

Figure Captions

Figure 1. Power functions fit to the mean correct RT data (left) and the corresponding standard deviation data (right) obtained in experiment one. The values of c given refer to the learning rate parameter for the unfamiliar face data (◇ - - -◇) and the familiar face data (o - - - o).

Figure 2. Power functions fit to the quantiles of RT data for correct responses to familiar faces (left) and unfamiliar faces (right) from experiment one. The values of c given refer to the learning rate parameter.

Figure 3. Power functions fit to the mean correct RT data (left) and the corresponding standard deviation data (right) obtained in experiment two. The values of c given refer to the learning rate parameter for the unfamiliar face data (◇ - - -◇) and the familiar face data (o - - - o).

Figure 4. Power functions fit to the quantiles of RT data for correct responses to familiar faces (left) and unfamiliar faces (right) from experiment two. The values of c given refer to the learning rate parameter.

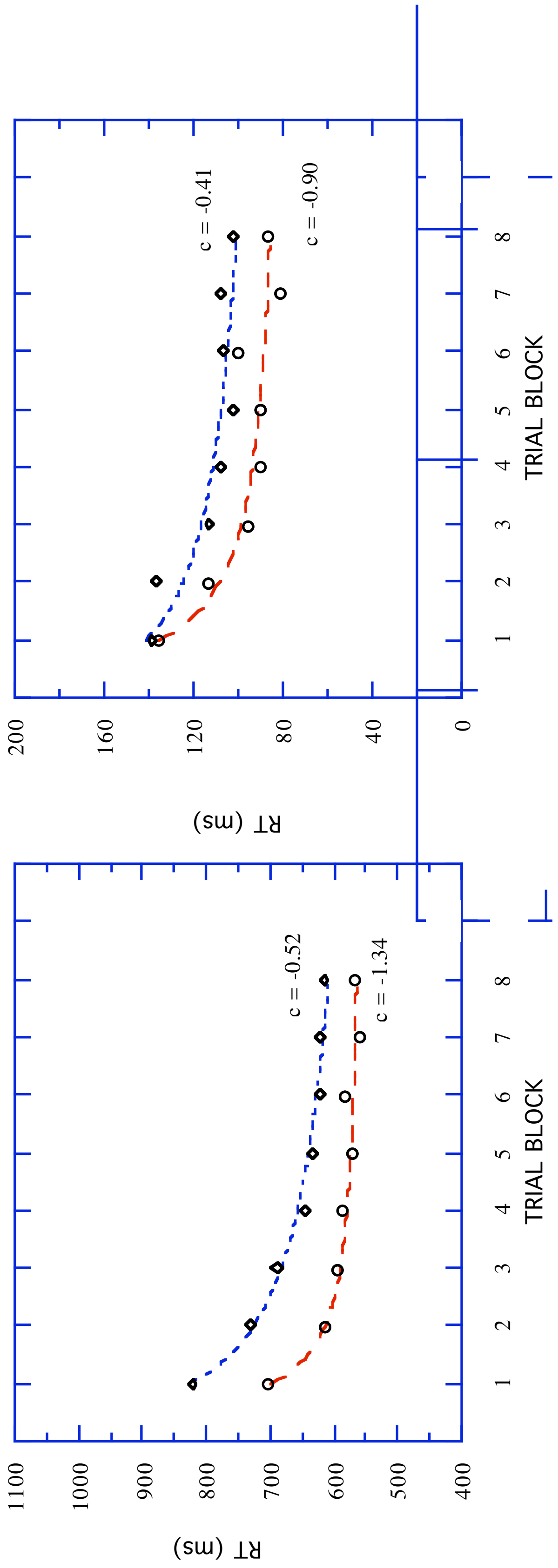

Fig 1.

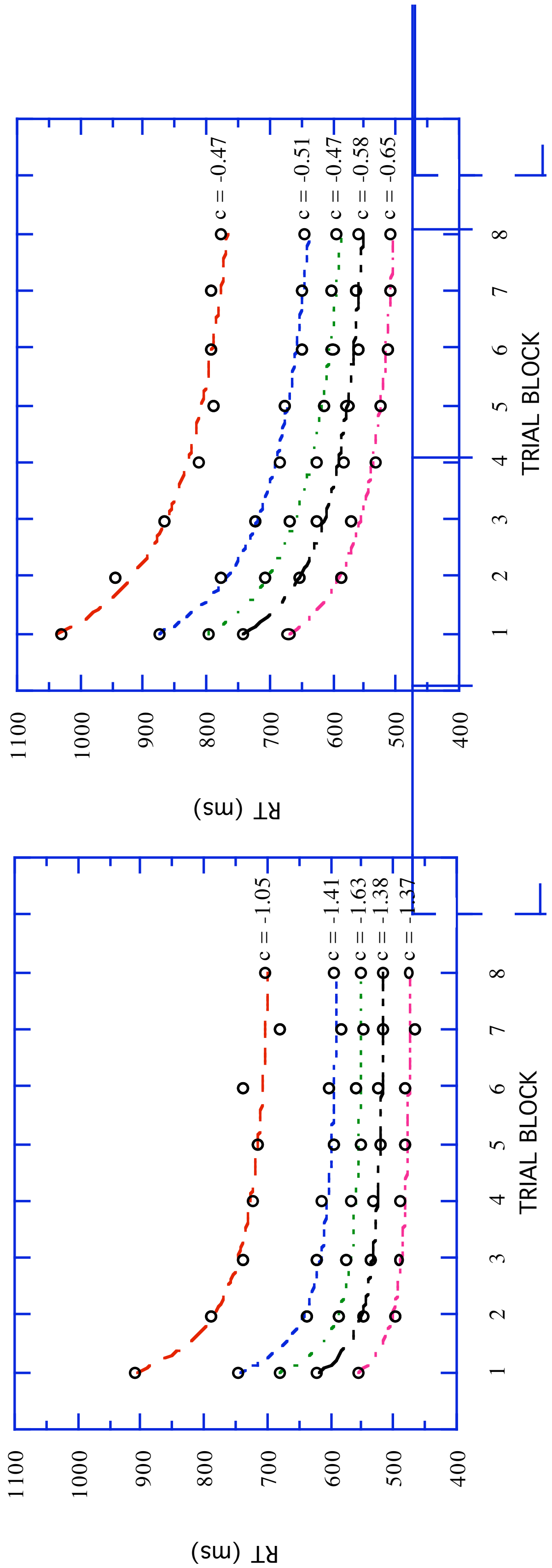
RT (ms)
TRIAL BLOCK
c = -0.47
c = -0.51
c = -0.47
c = -0.58
c = -0.65
c = -1.05
c = -1.41
c = -1.63
c = -1.38
c = -1.37

fig 2

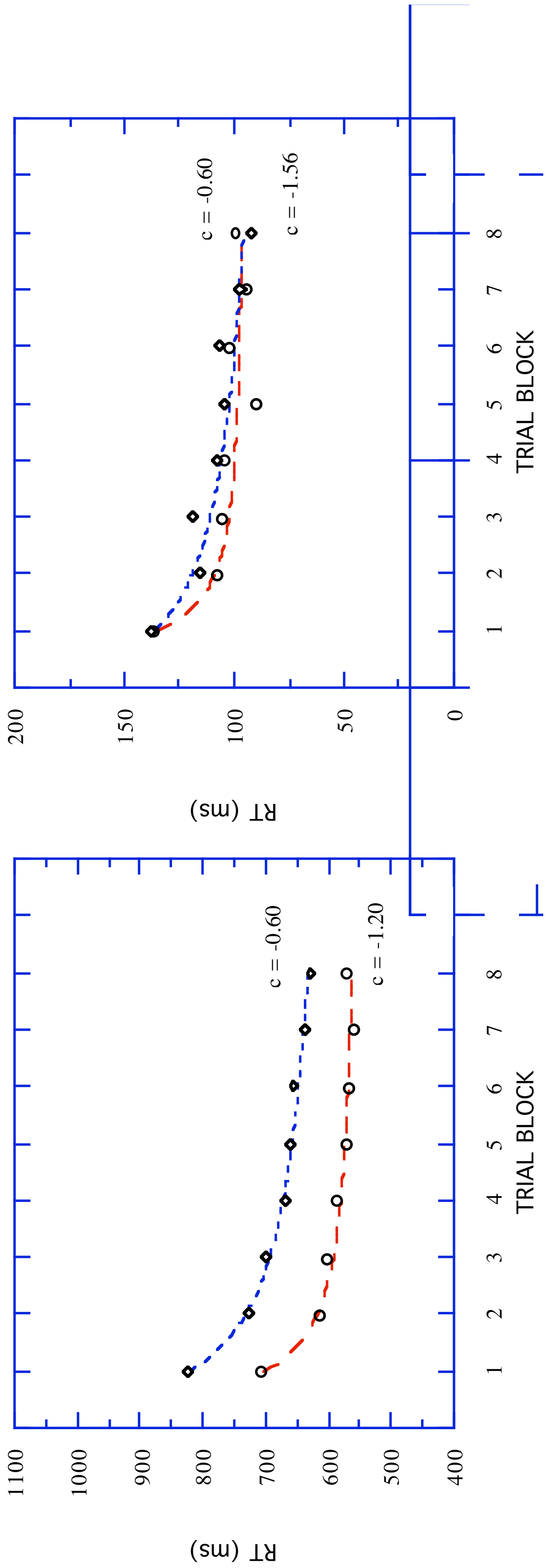

fig 3.

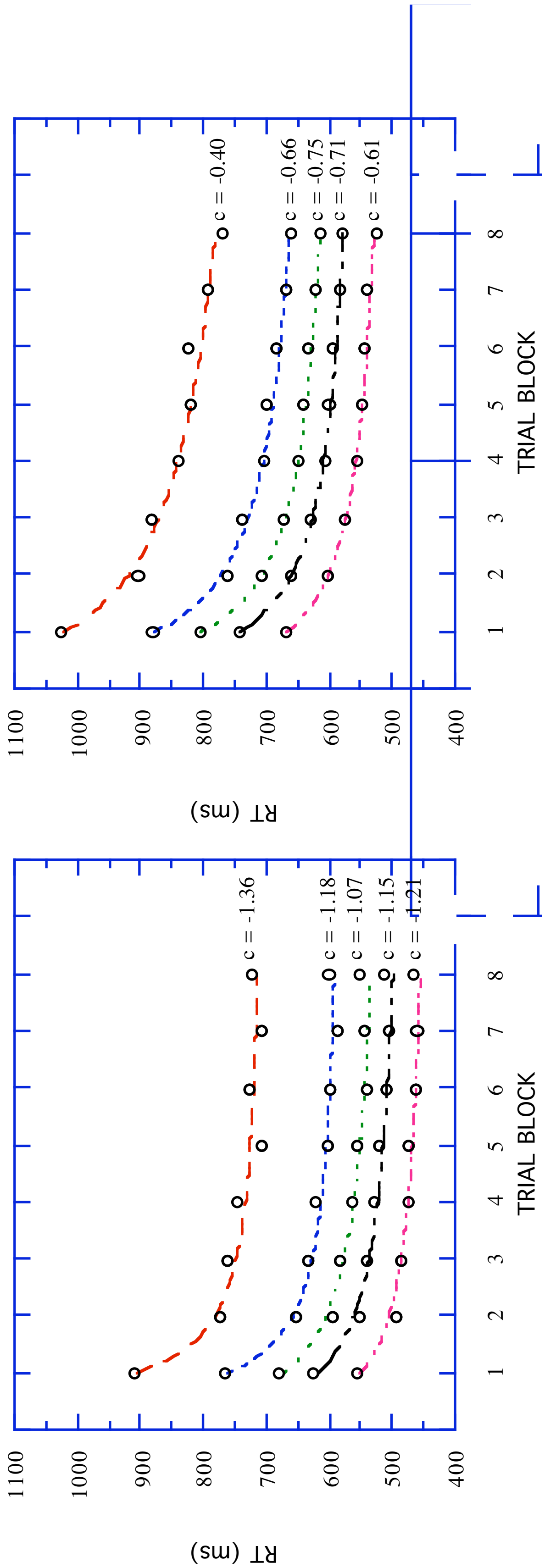
RT (ms)
TRIAL BLOCK
c = -0.40
c = -0.66
c = -0.75
c = -0.71
c = -0.61
RT (ms)
TRIAL BLOCK
c = -1.36
c = -1.18
c = -1.07
c = -1.15
c = -1.21

fig.4