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Running Head: Stimulus Probability Effects

Stimulus Probability Effects in Absolute Identification

Christopher Kent

University of Bristol

Koen Lamberts

University of York

Christopher Kent

School of Experimental Psychology

University of Bristol

12a Priory Road, Bristol, BS8 1TU

United Kingdom

Tel: +44 (0) 117 92 88552

Fax: +44 (0) 117 92 88588

c.kent@bristol.ac.uk

Abstract

This study investigated the effect of stimulus presentation probability on accuracy and response times in an absolute identification task. Three schedules of presentation were used to investigate the interaction between presentation probability and stimulus position within the set. Data from individual participants indicated strong effects of presentation probability on both proportion correct and response times. The effects were moderated by the ubiquitous stimulus position effect. The accuracy and response time data were predicted by an exemplar-based model of perceptual cognition (Kent & Lamberts, 2005). The bow in discriminability was also attenuated when presentation probability for middle items was relatively high, an effect which will constrain future model development. The study provides evidence for item specific learning in absolute identification. Implications for other theories of absolute identification are discussed.

Key Words: Absolute identification, stimulus frequency, presentation probability, mathematical model, exemplar theory

## Stimulus Frequency Effects in Absolute Identification

Absolute identification is a simple task in which participants must learn to identify stimuli that vary along a single relevant psychological dimension (such as length, pitch, saltiness, or roughness). The correct response for each stimulus is typically the ordinal position of the stimulus within the set of to-be-identified stimuli, with the set ordered by magnitude on the relevant dimension. Although absolute identification has been studied for over 80 years (Weaver & Zener, 1928, is probably the first article to report an absolute identification task in its recognized form), it remains an active, and often controversial, area of exploration (e.g., Brown, Marley, Donkin, & Heathcote, 2008; Dodds, Donkin, Brown, & Heathcote, 2011; Dodds, Donkin, Brown, Heathcote, & Marley, 2011; Kent & Lamberts, 2005; Lacouture & Marley, 2004; Petrov & Anderson, 2005; Rouder, Morey, Cowan, & Pfaltz, 2005; Stewart, Brown, & Chater, 2005). Along with this sustained interest in absolute identification there has been a shift in focus to consider not only measures of accuracy, but also measures of the temporal dynamics of absolute identification (e.g., Brown et al., 2008; Karpiuk, Lacouture, & Marley, 1997; Kent & Lamberts, 2005; Lacouture & Marley, 2004; Nosofsky, 1997).

One reason for the enduring interest in absolute identification is that, in order to complete the task, participants must utilise basic cognitive processes common to many other, often more complicated, psychological tasks. Despite the perceived simplicity of the task participants fail, often dramatically, to maintain perfect performance when the set of to-be-identified items increases beyond about five items (e.g., Miller, 1956). The task continues to provide a rich and challenging set of data for testing mathematical models of basic cognitive processes (see, e.g., Stewart et al., 2005, for a review). The most ubiquitous finding is that once performance drops below ceiling (at  $N > 5$ ), a bow is evident in both accuracy and response times (RTs) when either is plotted as a function of stimulus position in the set: the

bow effect. Stimuli at the ends of the range are responded to faster and more accurately than those in the middle of the range. The bow effect has become a fundamental benchmark for all potential models of absolute identification. The effect appears to be largely driven by the distinctiveness of end stimuli. For example, Costall, Platt, and MacRae (1981) failed to find a bow effect when they used a set of tone stimuli that were designed such that each tone sounded louder than the previous tone in the set, but also that the first ‘quietest’ tone sounded louder than the last ‘loudest’ tone in the set (see Shepard, 1964, for the stimulus development, which can be considered an auditory version of the color circle).

Despite the inherent advantage in performance for stimuli nearer the ends of the range, attempts have been made to understand how performance for individual stimuli may be enhanced. One method of enhancing both the speed and accuracy of a response to an individual stimulus is to increase its presentation frequency (e.g., Bertelson & Tisseyre, 1966; Krinchik, 1974; Miller, 1998). We refer to this effect as the *stimulus probability effect*. A handful of studies have previously investigated the stimulus probability effect in absolute identification. These studies have provided mixed results, and typically focussed exclusively on accuracy and not RT (with the exception of Dodds, Donkin, Brown, Heathcote, & Marley, 2011). Further, no model has been explicitly shown to provide an account of stimulus probability effects in absolute identification.

In this article, we briefly review the previous studies that have manipulated stimulus probability. We then describe a novel set of data, and provide an account of the data using an existing model, the Extended Generalized Context Model for Response Times (EGCM-RT, Kent & Lamberts, 2005) to predict both RTs and accuracy.

Cuddy, Pinn, and Simons (1973) compared performance between two conditions in an absolute identification task (nine tones differing in pitch). In the first condition, all stimuli were presented with equal probability, yielding the typical bow effect in discriminability. In

the second condition, the central stimulus was presented four times more frequently than the other stimuli. In the second condition, discriminability showed a bow effect, but also a small increase in accuracy around the central stimulus. Interestingly, the second condition resulted in higher accuracy across all stimulus positions.

Chase, Bugnacki, Braida, and Durlach (1983) replicated the Cuddy et al. (1973) experiment, but failed to find a significant effect of presentation probability. The Chase et al. (1983) study used 13 tones varying in loudness, and included three conditions: equal presentation probability across stimuli; the central stimulus was presented on one third of all trials; and the end stimuli were presented on one fifth of all trials. Although Chase et al. reported a response bias towards the more frequently presented stimuli, they found no effect of presentation probability on sensitivity (as measured by  $d'$ ).

Nosofsky (1983) reported results from an absolute identification task with 11 tones varying in loudness. Among other conditions, Nosofsky tested the difference between an equal presentation probability condition and a condition where two central stimuli were presented on one quarter of all the trials. Nosofsky found elevated levels of sensitivity around the centre of the range in the unequal presentation frequency condition, relative to the equal presentation probability condition. Again, these results represent a small stimulus probability effect.

Petrov and Anderson (2005) manipulated presentation schedules over blocks of trials to investigate sequential effects in absolute identification (see e.g., Stewart et al., 2005). Petrov and Anderson (2005) found that participants shifted their response bias toward the most frequently presented items. However, Petrov and Anderson (2005) used only positively and negatively skewed distributions, and manipulated the distributions between blocks and within participants, which makes the data unsuitable for analysis to investigate the effect of

presentation frequency on individual stimuli. Petrov and Anderson (2005) also only ever presented stimuli in the middle of the range with a mid-range probability.

Recently, Dodds and colleagues (Dodds, Donkin, Brown, Heathcote, & Marley, 2011) increased the amount of learning afforded to the central two stimuli, while keeping the presentation probability in any block of trials constant across the set of eight stimuli. Dodds and colleagues reasoned that if performance can be improved in absolute identification task (as shown by Dodds, Donkin, Brown, & Heathcote, 2011, and Rouder et al., 2004; despite the typical finding that participants do not improve throughout the task, e.g., Miller, 1956; Shiffrin & Nosofsky, 1994), then it should be possible to train participants on the central items in a pre-session and improve performance for those stimuli in a subsequent session among the rest of the (untrained) stimuli. Dodds and colleagues demonstrated a small, but reliable, increase in performance for the central two stimuli when they had been previously practiced in isolation.

From the few studies that have investigated stimulus probability effects in absolute identification, it appears that the effect of stimulus probability is less consistent and not as strong as is typically reported in other tasks. Additionally, only one study (Dodds, Donkin, Brown, Heathcote, & Marley, 2011) has looked at RTs and reported only a limited impact of prior learning on the RT bow effect. Response times are often a more sensitive measure than discriminability or proportion correct, and typically show large effects of presentation probability (e.g., Bertelson & Tisseyre, 1966; Krinchik, 1974). Previous studies have also not varied the pattern of presentation frequency (the distribution of presentation frequencies across stimulus position) that would allow a comprehensive examination of how presentation probability may interact with stimulus position. Only the Chase et al. (1983) study examined presentation probability at both the middle and the ends of the stimulus range. In the study reported here, we manipulated presentation frequency across the whole range of stimuli.

There are currently two exemplar-based models of the choice proportions and RTs in absolute identification that make explicit predictions about the stimulus probability effect, the EGCM-RT (Kent & Lamberts, 2005; based on Lamberts, 2000) and the Exemplar-Based Random Walk model (EBRW; Nosofsky, 1997, based on Nosofsky & Palmeri, 1997). Both models make the assumption that previously encountered stimuli are stored and represented in memory (both are extensions of the Generalized Context Model, Nosofsky, 1986). Although the models make different assumptions about the processes acting at the retrieval and choice stages of stimulus identification, both models predict that more frequently presented stimuli will have stronger representations in memory, and hence will be responded to faster and more accurately. In this study, we used the EGCM-RT to model stimulus probability effects, because the EBRW requires an additional assumption to capture the basic bow effect (assuming that noise is proportional to stimulus position), does not have an analytic solution for application to absolute identification, and has not been applied as widely as the EGCM-RT to absolute identification data.

In the study reported here, we used a design similar to Kent and Lamberts (2005) with 10 pairs of dots differing in distance apart as stimuli. The main difference between this study and Kent and Lamberts' (2005) experiments was the use of three different presentation probability schedules, one with increasing presentation frequencies towards the middle of the range, one with increasing presentation frequencies towards the ends of the range, and one with alternating high-low presentation probabilities across the range. These stimulus probability schedule distributions allowed us to investigate the interaction between stimulus position and stimulus probability.

## **Method**



*Participants.* Six postgraduate students and members of staff (5 female and 1 male, aged 22 to 29) from the University of Warwick participated in return for payment of £5 (approx. \$8) per hour.

*Materials.* Stimuli were presented on a calibrated 17" Cathode Ray Tube monitor, with a resolution of 800 x 600 pixels and a refresh rate of 60-Hz. Viewing distance was 30 cm from the center of the monitor. A chin rest was used to standardize visual angle. The room was dimly lit at all times. A voice switch (QED 2000 Ltd) was used to record RTs. The voice switch was connected to one of the ports of an Intel computer used to control the experiment, which allowed us to record RTs with millisecond accuracy. A tape recorder was used to record participants' verbal responses, and to ensure that participants were reliably inputting the same keyed response as their verbal response. Participants used a standard 102-key keyboard to input their responses and start each trial.

*Stimuli.* Stimuli were pairs of white dots (2 x 2 pixel squares) separated by one of 10 distances. The distance between the dots was the relevant dimension for identifying each stimulus. All stimuli were labelled according to their ordinal position from lowest to highest magnitude. The lowest magnitude stimulus ("One") was 92 pixels wide and the highest magnitude stimulus ("Ten") was 324 pixels wide (a range of 3.7 cm to 13.0 cm, or 7.4° to 25.7° visual degrees). The difference in distance between any two adjacent stimuli in the set was 15%. The midpoint between the two dots was the vertical and horizontal center of the screen. The background remained black throughout the experiment, whereas the dots and all visual feedback were presented in white.

*Design.* There were three conditions. In the Middle condition, the middle stimuli were presented five times more frequently than the end stimuli (Stimuli 1 and 10 were presented 100 times and Stimuli 5 and 6 were presented 500 times). Each stimulus between Stimulus 1 and Stimulus 5 was presented 100 times more frequently than the previous stimulus. Each stimulus between Stimulus 6 and Stimulus 10 was presented 100 times less than the previous stimulus. This resulted in a triangular frequency distribution with the apex at the centre of the set (see top panel of Figure 1). The End condition was the inverse of the Middle condition, with lowest presentation frequencies at the middle of the range. The middle stimuli were presented five times less frequently than the end stimuli (see middle panel of Figure 1). In the Alternating condition, stimulus positions had alternating high and low frequency distributions. Stimulus 1 had 100 presentations, Stimulus 2 had 500 presentations, Stimulus 3 had 100 presentations, and so on. Therefore, the difference in frequency of presentation between successive stimuli was 400 (see bottom panel of Figure 1). Two participants completed each condition. The presentation ratios of the stimuli remained fixed within each successive block of 300 trials. There were 10 blocks in total.

*Procedure.* Each trial started with a 1,000 Hz tone played for 100 ms. There was then a random delay between 500 ms and 1,000 ms. The stimulus was then presented. Participants were told to respond verbally to each stimulus with the prefix “It’s” followed by the stimulus label. For example, if Stimulus 3 was presented, the participant should respond “It’s Three”. Voice onset caused the voice switch to be activated. Once the voice switch was activated the stimulus disappeared from the screen. After a 500 ms delay, the words “Enter response” appeared on the screen. Participants then entered their first verbal response via the numbered keypad (the 0 key was used for response Ten). Pressing the Enter key then confirmed their

response. After 1,000 ms the correct response appeared at the centre of the screen for 1,000 ms. There was an inter-trial interval of 2,000 ms.

### Results

Responses made before 250 ms and after 6,000 ms from stimulus onset were excluded from further analysis, resulting in 0.13%, 0.37%, 2.5%, 0.23%, 0.2%, and 0.7% of the data from each participant, respectively, being excluded. There were too few correct trials for many of the low frequency stimuli for a reliable RT analysis. Therefore, only mean RT was investigated. The pattern of data reported below was not attributable to an increase or decrease in the number of repetitions (i.e., the same stimulus appearing on the current trial and on the previous trial) for each stimulus. When repetitions in the data (2,207 in total) were removed the pattern of results remained virtually unchanged (there was an average drop of 0.64% in accuracy and an increase of 12 ms in RT).

Figure 2 shows the proportion of responses for each stimulus for all the participants (confusion matrices, columns 1 and 3). For the Middle condition the bow effect in accuracy is attenuated and flattened for Participant 1 (with the exception of the end Stimulus 1) and has reversed for Participant 2, with higher accuracy in the Middle of the range (with the exception of the end Stimulus 10). The Middle condition shows that central stimuli are more accurately responded to if they are presented with a higher probability, attenuating or even reversing the bow effect.

For the End condition Participant 3's data were suggestive of a bow. However, the large negative response bias toward the lower end of the range created an asymmetry in the data, although responses to the end stimuli were still the most accurate. For Participant 4, there was a clear bow effect, with central and less frequently presented stimuli yielding lower accuracy than end stimuli and frequently presented stimuli. It is difficult to know whether the

bow is due to stimulus position or frequency of presentation. Compared with the data from Experiment 1 of Kent and Lamberts (2005; see Figure 1, Panels A, C, and E), which is most closely related to the current data, there does seem to be a small increase in accuracy for end stimuli and a decrease in the middle of the range, as might be expected. The difference in average proportion correct between the end stimuli (Stimuli 1 and 10) and the middle stimuli (Stimuli 5 and 6) in Kent and Lamberts' (2005) Experiment 1 was .14, and in the End condition it was .21 (averaged across participants), so the bow appears to be steeper in the End condition. Of course, this finding should be interpreted with caution, given the large between-participant differences and small number of participants.

For the Alternating condition, Participants 5 and 6 showed very strong frequency effects (although there still was a slight bow effect). When stimulus presentation frequency was high, accuracy was higher than when frequency was low. Overall, there was an effect of frequency on proportion correct, whereby more frequently presented stimuli were responded to more accurately than less frequently presented stimuli. The underlying bow effect was attenuated when the stimulus probability effect conflicted with the stimulus position effect.

Figure 2 (columns 2 and 4) show the mean RT data for each stimulus for each participant (correct and incorrect RTs showed a similar qualitative pattern, and we therefore report mean RT across both correct and incorrect trials). For the Middle condition the RT bow is attenuated compared with Experiment 1 of Kent and Lamberts (2005; see Figure 1, Panels B, D, and F), who found an average difference between end stimuli (Stimuli 1 and 10) and central stimuli (Stimuli 5 and 6) of 375 ms, and an average in the Middle condition of this experiment of 199 ms (averaged across participants). Thus, the RT bow in the Middle condition appears to be attenuated, although there is still a weak bow suggesting that even though the accuracy bow was reversed the RT bow is more resilient. This difference in the

pattern of results for accuracy and RT could be an important constraint for models of absolute identification.

For the End condition, there was a very strong bow effect in the data, with the end stimuli producing much faster RTs than central stimuli. Compared with Experiment 1 of Kent and Lamberts (2005; see Figure 1), the bow is much steeper: the average difference between End stimuli (Stimuli 1 and 10) and central stimuli (Stimuli 5 and 6) in Kent and Lamberts' Experiment 1 was 375 ms whereas the difference in the End condition of this experiment was 1006 ms (averaged across participants). Thus, frequency of presentation had a strong effect on the RTs in the End condition, with high frequency stimuli having faster RTs than less frequent stimuli.

For the Alternating condition, there was an effect of presentation probability on stimulus RT for both Participants 5 and 6: more frequent stimuli (the even-numbered stimuli in this condition) produced faster RTs than less frequent stimuli (odd stimuli). The effect can be seen for all pairs of stimuli that share the same relative position in the bow, for example Stimuli 1 and 10, Stimuli 2 and 9 etc., with the more frequent stimulus of the pair having the faster mean RT. There is still a slight bow effect with low frequency end stimuli responded to quicker than low frequency central stimuli.

Figure 3 shows  $d'_{i,i+1}$  (calculated according to Luce, Nosofsky, Green, & Smith, 1982) between adjacent pairs of stimuli ( $i$  and  $i+1$ ). The  $d'_{i,i+1}$  bow typically shows improved discriminability towards the ends of the range compared with the ends. In the Middle and Alternating condition the  $d'_{i,i+1}$  bows were attenuated compared with typical bows (see e.g., Lacouture & Marley, 1995; Luce et al., 1982; Stewart et al., 2005). Because discriminability is calculated between adjacent stimuli, the Alternating condition shows a relatively flat bow, with some evidence for improved discriminability towards the ends of the range for both Participant 5 and 6. For the End condition, as with proportion correct and RT, there is a

strong bow effect in discriminability. For the Middle condition, as with proportion correct and RT, the bow appears attenuated, with Participant 1 showing some evidence of improved discriminability between stimuli 1, 2 and Participant 2 for stimulus pair 9, 10.

Overall, the bow effect was evident in the End and Alternating condition, despite a large effect of presentation probability in the Alternating condition. For the Middle condition, the bow effect was attenuated, but for the very end stimuli (stimulus 1 for Participant 1 and Stimulus 10 for Participant 2) there still appeared to be an advantage, despite these being the least frequent stimuli.

### **Model Based Analysis**

The EGCM-RT is an exemplar-based model of choice response times for speeded classification (Lamberts, 2000). The model is fully described by Lamberts (2000) and a review of the success of the model can be found in Kent, Guest, Adelman, and Lamberts (2014). Here we describe the model as it is applied to absolute identification, following Kent and Lamberts (2005). In the EGCM-RT, information about the position of a stimulus along the range is assumed to be contained in a number of discrete, undifferentiated information elements (we assume five elements in our application of the model here, and elsewhere, as this provides a reasonable compromise between model accuracy, tractability, and fitting time). Elements are sampled stochastically and accumulated over time to help distinguish which stimulus is currently presented. The probability of an element  $\varepsilon$  being sampled at or before time  $t$  since stimulus onset is given by an exponential function:

$$I_{\varepsilon}(t) = 1 - e^{-q(t-t_{res})}, \quad (1)$$

in which  $q$  is the rate at which elements are sampled and  $t_{res}$  represents a constant amount of non-perceptual processing time (including any motor response time). All else being equal, the larger  $q$  the faster information is accumulated and the sooner sampling finishes and a response is given. The decision to stop sampling and make a response is determined by the relative evidence for one response over all other responses:

$$P(Stop | i, \varphi_t) = \frac{\sum_{j=1}^N [\zeta_j s_{ij}(\varphi_t)]^\theta}{\left( \sum_{j=1}^N [\zeta_j s_{ij}(\varphi_t)] \right)^\theta}, \quad (2)$$

where  $N$  is the number of stimuli,  $\theta$  determines the threshold for stopping ( $\theta \geq 1$ ),  $\zeta_j$  acts to increase or decrease the likelihood of giving response  $j$  and is linked to both the frequency and recency of stimulus  $j$ , with more frequent stimuli having larger  $\zeta_j$ , and  $s_{ij}$  is the similarity between stimulus  $i$  and stored exemplar  $j$  after the set of elements  $\varphi$  has been sampled at time  $t$ . The similarity between stimulus  $i$  and response  $j$  is calculated as:

$$s_{ij}(\varphi_t) = \left( e^{-c\varphi_t d_{ij}} \right)^\alpha, \quad (3)$$

in which  $c$  acts to scale the discriminability between exemplars,  $d_{ij}$  is the distance between stimulus  $i$  and exemplar  $j$ , and  $\alpha$  determines the relationship between distance and similarity. Further, Kent and Lamberts (2005) demonstrated it was necessary to assume a diminishing return of information with each additional element sampled:

$$\varphi_t = 1 - \lambda^n, \quad (4)$$

in which  $\lambda$  is the base of a decreasing power function relating the number of elements sampled to the amount of information accumulated. Thus the probability of giving response  $k$  ( $R_k$ ) to stimulus  $i$  after time  $t$  depends on the similarity between stimulus  $i$  and the representation of stimulus  $k$  with the distance between mismatching stimuli growing as a function of time and the frequency of presentation of stimulus  $k$ :

$$P(R_k | i, \varphi_t) = \frac{\zeta_k s_{ik}(\varphi_t)^\theta}{\sum_{j=1}^N [\zeta_j s_{ij}(\varphi_t)]^\theta} . \quad (5)$$

In order to apply the model to our data we need to specify what the function relating stimulus frequency to  $\zeta$  is. A parsimonious method would be to assume a linear function between presentation probability and  $\zeta$  such that the similarity is multiplied by the presentation probability. To test whether this assumption would allow the EGCM-RT to simultaneously fit the choice proportion data and RTs for each individual, a five-parameter model was used with  $\zeta_j$  determined by the probability of presentation for stimulus  $j$ . For example, in the Middle condition  $\zeta_5 = .166$  and in the End and Alternating conditions  $\zeta_5 = .033$ . The five free parameters were:  $c$ ,  $\theta$ ,  $q$ ,  $\alpha$ , and  $\lambda$  (following Kent and Lamberts, 2005, we set  $t_{res}$  to be fixed across participants at 250 ms). To estimate the best fitting parameters we minimised the joint sums of squares for the model predictions of both choice proportions and RT. To address the fact that RTs and choice proportions are on different scales, we divided the RT sums of squares by the total sums of squares for RT before summing it with the accuracy sums of squares. In order to constrain the model fitting, we only allowed  $\theta$  to vary across participants, allowing individual differences in how deterministic responding was. Thus, 660 data points were predicted with 10 free parameters.



The predicted choice proportions and RT from the model are illustrated in Figure 2 (broken lines) along with the data. The best fitting parameter values are given in Table 1. For the Middle condition, the model predicts a shallow but inverse bow in accuracy. The model cannot predict the asymmetries in the bow (increased accuracy for Stimulus 1 and 10 for Participants 1 and 2 respectively). Such asymmetries are often seen for individual participants, but their nature is typically idiosyncratic and an attempt to systematically model them is unlikely to reveal new insights. The model correctly predicts a reduced (flat) bow effect in RT for both participants in the Middle condition, missing slightly the increased speed for end stimuli. The model correctly predicts the pattern of data in the End condition, predicting strong bow effects in both accuracy and RT. Again, the model misses the asymmetry in Participant 3's data. For the Alternating condition, the EGCM-RT correctly predicts the highest accuracy and fastest RTs for the more frequent stimuli, in addition to a small bow effect. For Participant 5, the model mis-predicts that the less frequent stimuli are responded to more often with a high frequency neighbour rather than the correct response. However, this is the result of restricting parametric variability across participants, rather than a necessary predication of the model. Letting  $c$  or  $\lambda$  vary between Participants 5 and 6 allows the model to correctly predict the distinct patterns of responding. Nonetheless, overall the EGCM-RT provides a good account of the choice proportions and RTs. Allowing additional parameters to vary between participants and conditions would improve model fit further. However, given that the major qualitative patterns are predicted by the 10-parameter model, we do not explore less constrained models here.

The model was able to capture the very different patterns of choice and RT data in the three conditions by only changing the multiplier in the choice ratio. Importantly, this parameter was completely determined by the experimental design. The only flexibility across individual data sets was in the  $\theta$  parameter, which enables the model to capture individual

differences in how deterministic responding is. Table 1 shows that this parameter took similar values for all 6 participants (ranging from 1-1.64). The remaining parameter values are broadly in line with those from previous model applications to similar data sets (e.g. Kent & Lamberts, 2005).

An important limitation of the EGCM-RT is that it has no mechanism to predict the bow in  $d'_{i,i+1}$  (Figure 3). The model predicts flat, or slight inverse bows in  $d'_{i,i+1}$ . This is the result of using equal spacing between stimulus representations in the modelling. As highlighted by Nosofsky (1997) exemplar models need a psychological scaling solution for the representation of exemplars in memory. Such a scaling solution would require further work mapping stimuli to psychological space, leading to a detailed model of how exemplars are represented in memory. In his exemplar model Nosofsky (1997) assumed that the variance associated with each stimulus representation is a function of its distance from the ends of the stimulus range. A similar mechanism could work in the EGCM-RT. However, currently the memory aspect of the EGCM-RT is underdeveloped and additional work is required to develop a more complete memory process of the EGCM-RT. For example, including a mechanism through which the rate at which information is accumulated from memory is partly determined by the strength of the memory representation, which depends upon its overall dissimilarity to other exemplars can produce a bow in  $d'_{i,i+1}$  (see Guest, Kent, & Adelman, 2015).

### Discussion

The data showed a large effect of the probability of presentation of a stimulus on both choice proportions and RT in an absolute identification task. Increased presentation probability led to an increase in accuracy and a decrease in RT. This was demonstrated in all three conditions. The bow effect was attenuated when presentation frequency was higher in the

middle of the range than at the ends of the range (Middle condition). The bow effect was extended in magnitude when presentation frequency was lowest in the middle of the range and highest at the ends of the range (End condition). When stimuli alternated between high and low probability, the bow effect was still present but only for stimuli of equal presentation frequency (Alternating condition). A similar pattern of data was seen when  $d'_{i,i+1}$  was plotted instead of proportion correct, suggesting the effect of increasing presentation probability, also increased sensitivity for more frequently presented stimuli.

The EGCM-RT offered a good account of the full response matrix and RTs without any alterations to the existing model. To capture the frequency effects, the EGCM-RT assumes that  $\zeta_j$  is proportional to the total number of presentations of stimulus  $j$ . A more complex relationship may exist between the absolute frequency of presentation and  $\zeta$ , but for now the simple assumption of proportionality provides a good account of the data. The frequency effect was predicted because  $\zeta_j$  acts to increase the probability of responding  $j$  if  $\zeta_j$  is large relative to other  $\zeta_k$ . Thus, less information has to be accumulated before response  $j$  is given, and hence RTs are faster. The choices were also more accurate because the probability of giving a response with a high frequency of presentation was relatively higher than the probability of responses associated with lower frequency presentations. Accuracy was also lower for other stimuli because high frequency responses attract responses from neighbouring stimuli (see in particular the Alternating condition). However, the model does not yet offer an account of the bow in discriminability, and this is an important aspect of the data for future model development to account for.

The results suggest that the bow effect can be attenuated by increasing the number of presentations of stimuli in the centre of the range. Rouder et al. (2004) also found that practice affected middle stimuli more than end stimuli, and Dodds and colleagues (Dodds, Donkin, Brown, Heathcote, & Marley, 2011) demonstrated that practice on the middle stimuli

increased performance for those items relative to neighbours. Taken together, these results suggest that learning is stimulus specific. In other words, practice on certain stimuli leads to a stronger representation for those stimuli in memory, contrary to claims that the role of long-term representation in absolute identification is minimal (e.g., Stewart et al., 2005).

It is possible that another current model of absolute identification, the Selective Attention, Mapping, and Ballistic Accumulator Model (SAMBA; Brown et al., 2008) can be modified to make the prediction that stimuli with a higher presentation probability will be identified more accurately than those with a lower presentation probability. Dodds and colleagues (Dodds, Donkin, Brown, Heathcote, & Marley, 2011) suggested that the selective attention mechanism used to capture contrast effects might be able to explain longer term changes if it is assumed that more frequently presented stimuli have a privileged status in memory, with the psychological space expanded around them (see also models by Marley & Cook, 1984, and Luce, Green, & Weber, 1976). However, while this assumption will allow SAMBA to produce the pattern of data for the Middle and End conditions, it will not be able to produce the correct pattern for the Alternating condition, as in that condition the stimuli will still be equally spaced providing near equivalent performance for adjacent pairs (stretching space around the high frequency items will also cause the low frequency items to become more isolated). The EGCM-RT's solution does not change space, but only the perceived similarity between stimuli and exemplars. A similar solution in SAMBA would be to change the response strengths from the mapping process to depend on the stimulus presentation probabilities, or for the rate at which stimulus accumulators return to resting levels to depend on the stimulus presentation probabilities. Initial simulations show that these solutions would allow SAMBA to capture the higher accuracy for more frequently presented stimuli. However, these solutions did not produce the frequency effect for RTs. Instead, other elements of the model, such as the response thresholds, would also have to change as a

function of stimulus presentation probability, to enable SAMBA to capture faster responses for more frequently presented stimuli. Thus, currently, the EGCM-RT generally provides the most parsimonious account of frequency effects in absolute identification. However, SAMBA has the advantage of accounting for other aspects of the data (namely sequential effects, and the bow in discriminability) which the EGCM-RT does not explain. In addition, the memory mechanism in the EGCM-RT responsible for generating the bias for high frequency stimuli is under-specified. We have recently developed a more detailed memory mechanism for the EGCM-RT which entailed memory sampling in an analogous manner to perpetual sampling (Guest, Kent, & Adelman, 2015). However, the purpose of this study was not to rigorously test model implementations, but to show the importance of long-term representations more generally to performance in absolute identification. Clearly, further model development of both SAMBA and the EGCM-RT would be of interest to better understand the mechanisms underlying absolute identification. After 80 years, absolute identification remains a fertile ground for cognitive psychologists interested in the fundamental processes of stimulus encoding, representation, and decision making.

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Table 1. *Best Fitting Parameter Values for the EGCM-RT for All Participants*

Parameter	Condition					
	Middle		End		Alternating	
	Participant					
	1	2	3	4	5	6
$q$				.0003		
$c$				1.65		
$\alpha$				1.15		
$\lambda$				0.17		
$\theta$	1.00	1.17	1.17	1.64	1.48	1.20

*Note.*  $q$  is inclusion rate;  $c$  is discriminability value;  $\theta$  determines stopping probabilities;  $\alpha$  relates similarity to distance; and  $\lambda$  is the base of the power function relating the number of processed element to the amount of information accumulated.

**Figure Captions**

*Figure 1.* Frequency of presentation of each stimulus in the three conditions, Middle, End, and Alternating.

*Figure 2.* Confusion matrices (columns 1 and 3) and response times (columns 2 and 4) as a function of stimulus for each participant (P) in the Middle, End, and Alternating conditions (rows). Filled black lines are the data and broken grey lines are the EGCM-RT predictions.

*Figure 3.* Discrimination,  $d'_{i,i+1}$ , plotted for each adjacent stimulus pair (calculated according to Luce et al., 1982) in the three conditions, Middle (panels A and B), End (panels C and D), and Alternating (E and F) for each participant (P).

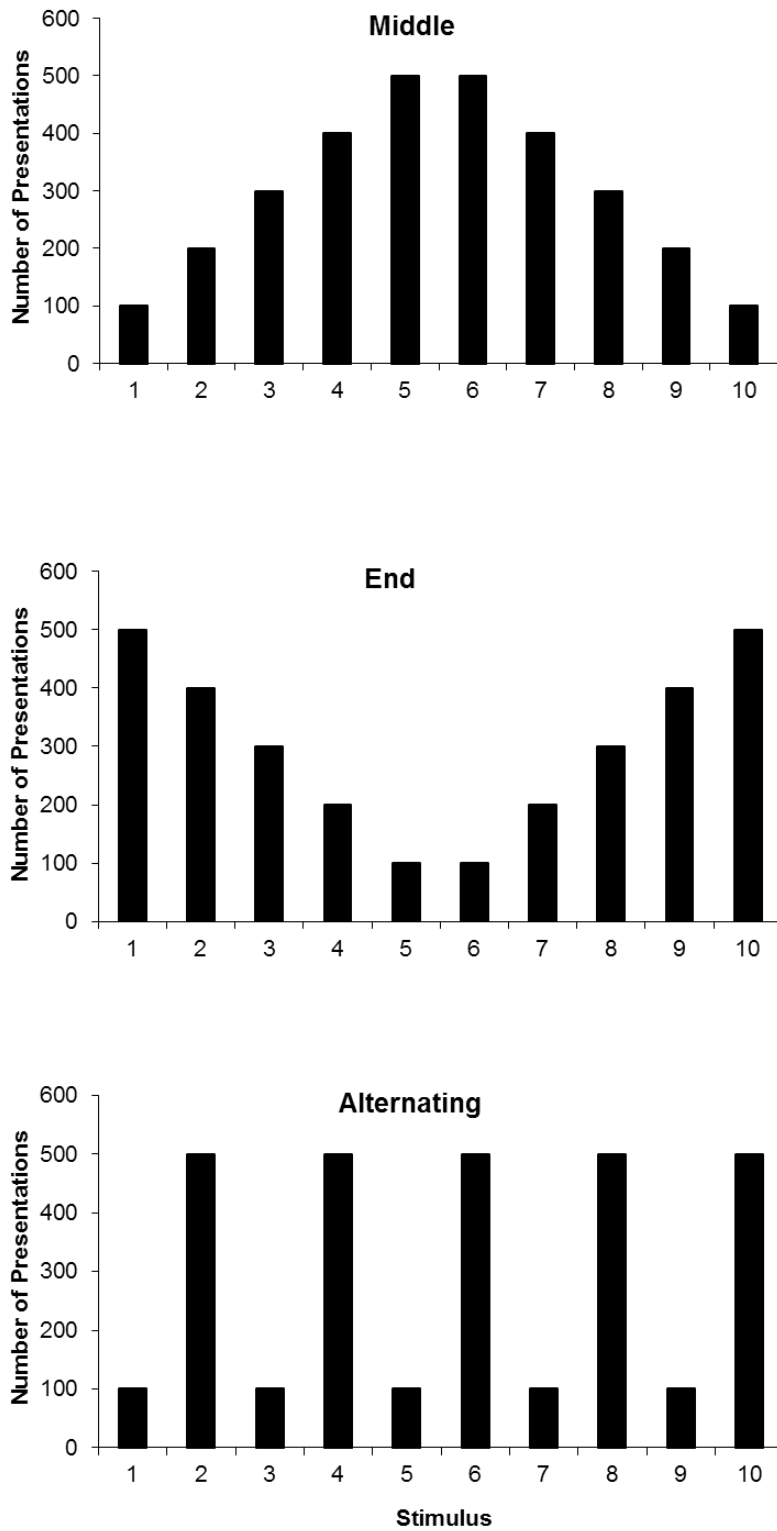


Figure 1.

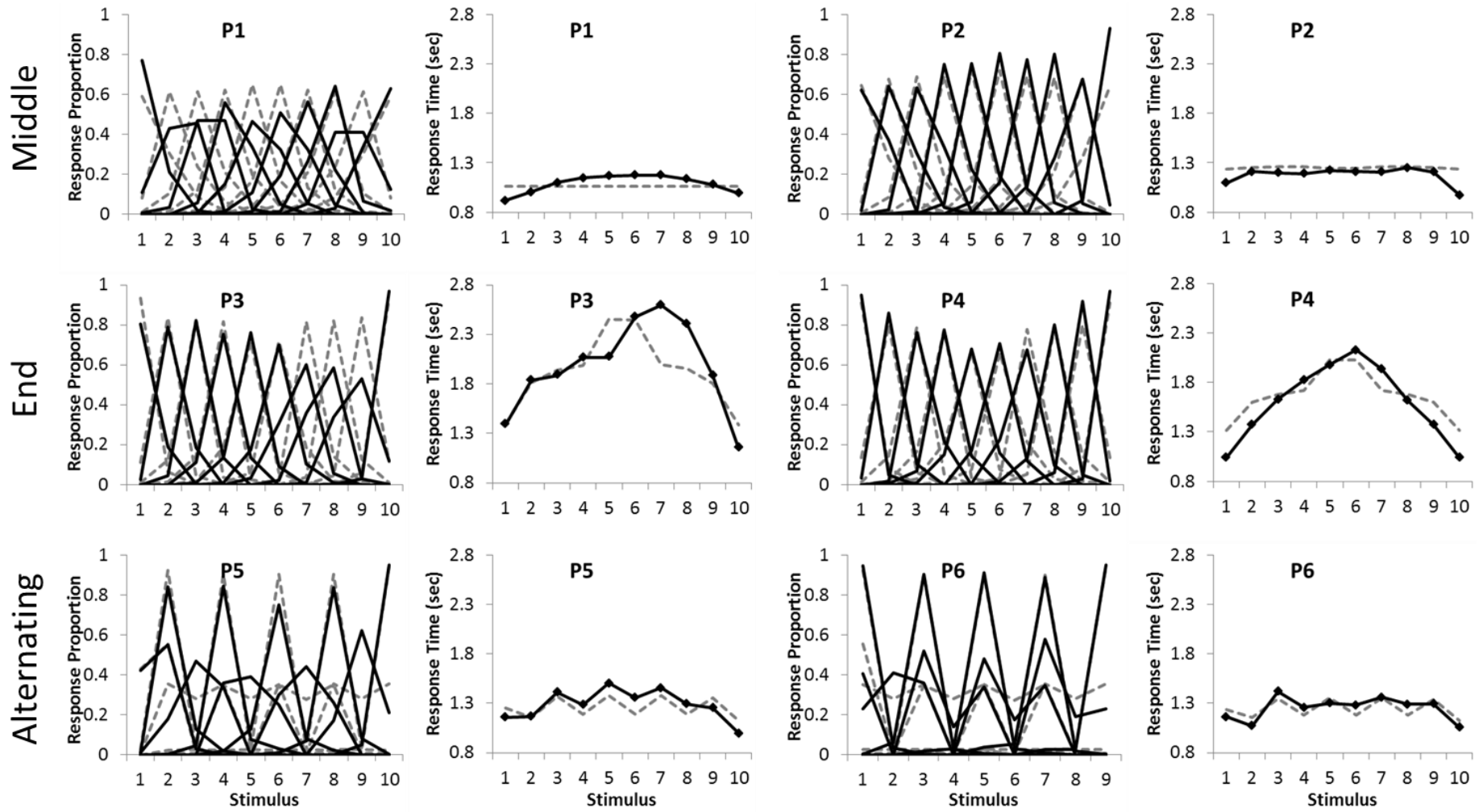


Figure 2.

Stimulus Probability Effects 1

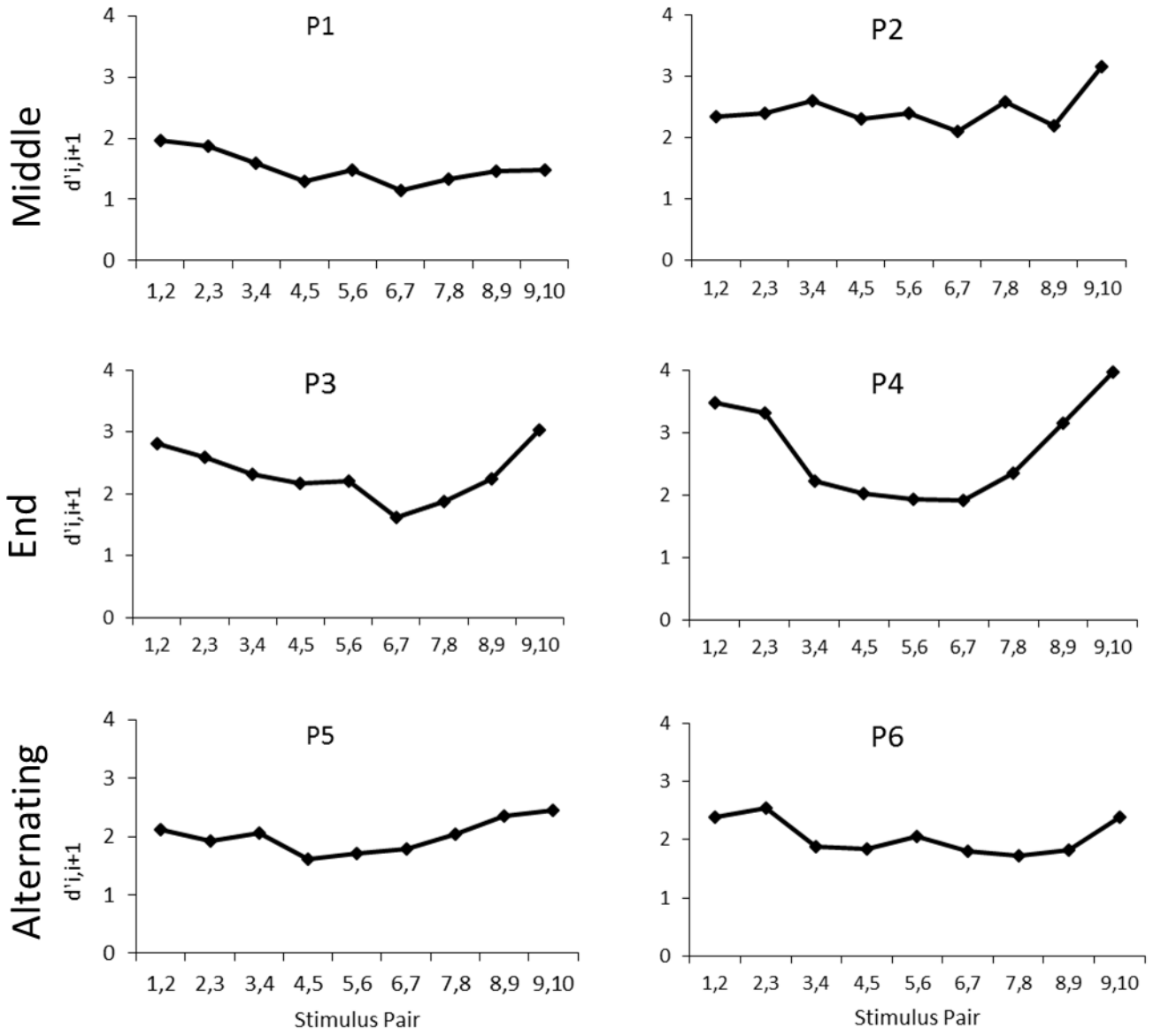


Figure 3.