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The relative importance of perceptual and memory sampling processes in determining the time course of absolute identification

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Authors

Duncan Guest, Christopher Kent and James S. Adelman

Corresponding Author

Duncan Guest

duncan.guest@ntu.ac.uk

Nottingham Trent University

Burton Street, Nottingham, UK

NG1 4BU

Tel: +44(0)115 84 82701

Abstract

In absolute identification, the EGCM–RT (Kent & Lamberts, 2005, 2016) proposes that perceptual processing determines systematic response time (RT) variability; all other models of RT emphasise response selection processes. In the EGCM-RT the bow effect in RTs (longer responses for stimuli in the middle of the range) occurs because these middle stimuli are less isolated and so as perceptual information is accumulated, the evidence supporting a correct response grows more slowly than for stimuli at the ends of the range. More perceptual information is therefore accumulated in order to increase certainty in response for middle stimuli, lengthening RT. According to the model reducing perceptual sampling time should reduce the size of the bow effect in RT. We tested this hypothesis in two pitch identification experiments. Experiment 1 found no effect of stimulus duration on the size of the RT bow. Experiment 2 used multiple short stimulus durations as well as manipulating set size and stimulus spacing. Contrary to EGCM-RT predictions, the bow effect on RTs was large for even very short durations. A new version of the EGCM-RT could only capture this, alongside the effect of stimulus duration on accuracy, by including both a perceptual and a memory sampling process. A modified version of the SAMBA model (Brown, Marley, Donkin, & Heathcote, 2008) could also capture the data, by assuming psychophysical noise diminishes with increased exposure duration. This modelling suggests systematic variability in RT in absolute identification is largely determined by memory sampling and response selection processes.

Keywords. Absolute identification, perceptual processing, memory sampling, response selection

The relative importance of perceptual and memory sampling processes in determining the time course of absolute identification

The last 30 years has seen the development of several detailed mathematical models of the time course of cognitive processes. These models specify how, over the time course of a cognitive process, information about a stimulus is sampled and integrated into a decision mechanism. Such models have been applied successfully to a wide range of cognitive tasks and have been influential in helping understand the processes underlying such tasks (e.g., Smith & Ratcliff, 2009). An important distinction between these models is the emphasis placed on what is being sampled. In some models, there is a great emphasis on the importance of perceptual processing (Adelman, 2011; Guest & Lamberts, 2010, 2011; Lamberts, 2000, Kent & Lamberts, 2005, 2006a, 2016). These models suggest that, over the time course of a trial, a representation of a stimulus is gradually built up through repeated sampling of the stimulus such that the information that is fed into the decision process changes over time. In such models (e.g., Lamberts, 2000) task performance at a given point in time is limited by the state of the perceptual representation of the stimulus at that time. Thus the time course of perceptual processing plays a major role in determining response latencies and the choices made.

In contrast, many other models of the time course of cognition assume that there is a relatively fast perceptual processing stage, followed by a decision stage in which either a single sample, or multiple samples, of the stimulus representation feeds through into the decision process. In these, sequential sampling, models the emphasis is on the dynamics of the response selection stage determining the time course of performance. Such models include random walk or diffusion models (e.g., Nosofsky

& Palmeri, 1997; Ratcliff 1978, Ratcliff & Rouder, 2000; Smith & Ratcliff, 2009; Smith & Sewell, 2013) and accumulator models (e.g., Brown, & Heathcote, 2005; Usher & McLelland, 2001). In sequential sampling models, response-relevant information drives the accumulation of evidence toward a particular response. This is typically instantiated by a response boundary representing the amount of evidence required for that response to be given. Accumulator models assume that there are multiple accumulators, each representing a possible choice, that race toward a response threshold (or a relative threshold defined by the difference between the winning and runner-up accumulator), with the first accumulator to reach this threshold determining the response given. The speed at which each accumulator moves towards the threshold is largely determined by the strength of evidence for that response. These models can assume a single sample of the perceptual representation of the stimulus, or multiple samples such that there is some within trial variability in the drift rate (the rate at which an accumulator moves towards the response threshold, e.g., Usher and McLelland, 2001) and some models also assume between trial variability in drift rate (Brown, & Heathcote, 2005).

An important issue is therefore the extent to which the time course of perceptual processing underlies performance in basic perceptual tasks (e.g., identification, categorisation and recognition). In this article, we explore this issue within the task of absolute identification. In absolute identification, multiple stimuli ($N > 2$) varying on a single psychophysical dimension (e.g., length of a line or pitch of a tone) are paired with numerical labels referring to their magnitude ranking in the set. On each trial, the participant attempts to respond with the label for the randomly selected stimulus. The task has long been of interest due to the surprisingly severe performance limitations when $N > 5$ (e.g., Cowan, 2001; Miller, 1956) and because the processes involved in it are fundamental and likely to underlie many other cognitive tasks. As such the task remains of interest (Brown et al. 2009; Dodds et al. 2011a, b; Donkin, Chan, & Tran, 2015; Guest, Adelman & Kent; 2016) and recently several detailed mathematical models of absolute identification have been developed (including Brown, Marley, Donkin, & Heathcote, 2008; Kent & Lamberts, 2005, 2016; Lacouture & Marley, 1995, 2004; Petrov & Anderson, 2005; Stewart, et al., 2005, Stewart & Mathews, 2009). Current models predict both choice proportions and full RT distributions. Standard effects that these models predict include the bow effect, whereby there are performance advantages (in accuracy and RT) for stimuli nearer the edges of the range, and the set size effect, whereby performance is better for smaller *N* (Brown et al., 2008; Kent & Lamberts, 2005; Lacouture & Marley, 2004). Importantly, models of absolute identification place different emphasis on the importance of either perceptual or response processes. In many models, perceptual processing is given a relatively minor role. For example, in the Selective Attention, Mapping, and Ballistic Accumulator model (SAMBA; Brown et al, 2008) it is assumed that perceptual processing takes a relatively small amount of time and that a relatively robust psychophysical representation enters response selection processes fairly quickly. In contrast, the time course of perceptual processing is central in the Extended Generalized Context Model (EGCM; Kent & Lamberts, 2005, 2016).

The EGCM was initially developed to account for the time course of categorization performance (Lamberts, 1998, 2000) extending the Generalized Context Model (Nosofsky, 1986). It assumes that, over time, perceptual information is gradually accumulated such that a representation of a stimulus evolves from an undifferentiated representation to a well-defined representation. As the stimulus representation evolves, so the similarity between the stimulus representation and exemplars in memory changes. These assumptions were supported in a number of investigations (e.g., Lamberts & Freeman, 1999) and the perceptual processing assumptions in the EGCM have since been used to successfully model the time course of performance in a number of related tasks including perceptual matching (Kent & Lamberts, 2006a, 2006b), recognition (Brockdorf & Lamberts, 2000) and visual search (Guest & Lamberts, 2011; see Kent et al. 2014 for a review). The model has also been extended from signal-to-respond to RTs in respond-when-ready paradigms by assuming that the decision to respond is made probabilistically on the extent to which the evidence accumulated favours a single response after each sample of evidence (Lamberts, 2000).

Kent and Lamberts (2005) extended the EGCM-RT to account for the bow and set-size effects in absolute identification. While providing a good account of the bow effects and set-size effects in choice and RT data, the EGCM-RT has only been applied to data from absolute identification tasks in which participants respond when ready, which provide little information about the dynamics of perceptual processing. To date, several studies shed some light on perceptual processing dynamics in absolute identification. Pollack (cited in Miller, 1956) found that increasing stimulus presentation duration from 25 ms to 5,000 ms improved identification of area, line length, and angle of inclination. However, Garner and Creelman (1964) reported no performance difference between 40 ms and 100 ms presentations in identification of square size or hue and Guest, Kent, and Adelman (2010) found that increasing stimulus duration from 250 ms to 500 ms had no influence on identification of tone pitch or line length. More detailed time course data indicate that performance reached asymptotic levels between 135-405 ms of stimulus duration in tone intensity identification and after 15 ms of stimulus duration for light intensity identification

(Ward, 1991) and after around 100 ms of stimulus duration for tone pitch (Hseih & Saberi, 2007).

These experiments provide some indication of the time course of perceptual processing in absolute identification (which is probably linked in some form to stimulus duration) but they did not report RTs or examine how performance changed across the stimulus range making it difficult to interpret the relationship between perceptual processing and RT. Measuring both response choice and RT for individual stimuli is essential in order to explore the importance of perceptual processes in determining the time course of performance. It also places significant constraints on models. In particular, due to its link between perceptual processing and RT, the EGCM-RT makes clear predictions when the time for perceptual processing is constrained. According to the EGCM-RT, in absolute identification the psychophysical dimension separates into several features, or information elements, each contributing to the psychological distance between different stimuli, but with diminishing returns such that later samples add less information with which to determine similarity between exemplars. The model links accuracy and RT because stimuli that are more difficult to identify, that is they have greater summed similarity to the entire set of stimuli than other stimuli (e.g., stimuli in the middle of the stimulus range), are perceptually sampled for longer in an attempt to maximise response certainty. However, as there is a diminishing information return on perceptual sampling, lengthening sampling time increases RTs but has a limited impact on accuracy. Thus, in the EGCM-RT, low response accuracy tends to be linked to longer RT, allowing the model to capture bow effects in both accuracy and RT. Kent and Lamberts (2005) showed the EGCM-RT was able to capture these bow effects across a range of set sizes through estimating a relatively lengthy perceptual processing time (approximately 1,100 ms) which accounted for the majority of the RT. Similarly, Kent and Lamberts (2016) estimated average perceptual processing time to be approximately 3,300 ms. Reducing the time available for perceptual processing should, according to the EGCM-RT, reduce both overall RTs and the size of the bow effect in RT because it will curtail the opportunity to carry on perceptual processing for stimuli for which a response is less certain, in this case, stimuli in the middle of the range that are less isolated in psychological space. However, this will have a larger effect on RT than accuracy, because additional perceptual processing yields diminishing information returns. The experiments reported in this article are designed to test this prediction that reducing the time available for perceptual processing should reduce the bow effect in RT whilst leaving the bow effect in accuracy relatively unchanged.

In two absolute identification of tone pitch experiments, we manipulated stimulus duration and stimulus spacing (wide or narrow spacing). Experiment 1 tested many participants with *N* = 8 tone frequencies with either a short (500 ms) or long (until response) stimulus duration. Experiment 2 extensively tested a few participants but also manipulated set size (*N* = 6 or 8) and a range of stimulus duration (from 10-300 ms). Neither experiment provided evidence that the RT bow effect was substantially reduced in magnitude in the short compared with the long stimulus duration conditions, contrary to the predictions of the standard EGCM-RT. In Experiment 2, although the magnitude of the bow remained relatively constant across durations, the overall accuracy increased with exposure duration. We developed a new EGCM-RT model which included a memory sampling process (the Perception and Memory EGCM-RT, PMEGCM-RT) that was able to capture both the increase in overall accuracy with duration, but also the magnitude of RT bow effect across durations by allowing for a long memory sampling time relative to perceptual sampling time.

We also developed a new version of SAMBA which included an assumption that perceptual noise reduces with increasing stimulus, allowing it to capture the increase in accuracy with stimulus duration (the standard SAMBA model already predicted no effect of stimulus duration on the magnitude of the RT bow). As SAMBA was also able to fit this data it retains its status as the benchmark model of absolute identification (it can account for the widest number of effects). However, SAMBA is a model specifically of absolute identification and a major research challenge is to develop a model that simultaneously handles absolute identification and other areas of cognition such as categorisation and recognition. The framework of our new model, the PMEGCM-RT, has parts that have previously been applied to categorization, recognition, perceptual matching, and visual search (see Kent et al., 2014, for a review) and so more work is required to examine how this new model can help explain the processes underlying these tasks.

Experiment 1

In Experiment 1, participants completed an absolute identification task using tones varying in pitch in which stimulus presentation time was manipulated between blocks. In one block of trials stimuli remained on screen until response (long duration), in the other they were presented for at most 500 ms (short duration).

Method

Participants. Sixty-four participants (average age 21), forty-three female, twenty-one male, completed the experiment for payment of £4 (approximately $6). Participants were students or members of staff at a British University or their friends and relatives.

Materials. A Pentium II computer was used for stimulus presentation and response registration. Participants sat 160 cm from the center of a 43.2 cm CRT monitor set at resolution of 1260 x 1024 pixels with a refresh rate of 60 Hz. Stimuli were presented in stereo over Plantronics Hi-Fi Audio 90 headphones. Responses were made via a keyboard using the number keys.

Stimuli. The stimuli were two sets of eight tones varying in frequency. The tones used were the same pitches as those used in the eight stimulus conditions of Stewart et al. (2005). In the wide spacing condition the frequency of the lowest tone was 672 Hz with each subsequent tone increasing in frequency by 12%. Thus, the wide tones had a total range of 813.58 Hz. In the narrow spacing condition the lowest tone was 814.82 Hz with each subsequent tone increasing in frequency by 6%. Thus, the narrow tones had a total range of 410.40Hz. In each spacing condition the frequency increased by a constant percentage and so the stimuli were equally spaced in log space and therefore approximately evenly spaced in psychological space. Furthermore, the centre of the range of the narrow-spacing condition in log space was the same as centre of the range of the wide-spacing condition. For half the participants, the tones were labelled Stimulus 1-8 with ranking from low to high tones; for the other half of the participants, the tones were labelled Stimulus 1-8, ranked from high to low tones.

In both duration conditions, when tones were presented the initial 50 ms was ramped linearly from silence to maximum amplitude. In the 500 ms exposure duration condition, the final 50 ms was ramped linearly from maximum amplitude to silence. In the variable exposure condition, a tone was played until a participant made a response. If a participant made no response for 30 s then the tone ended (any responses taking longer than 3,000 ms were not included in the analysis). When the participant made their response, the tone was silenced. In the standard exposure condition tone was also silenced when a response was made in less than 500 ms (1.54% of trials).

Design. Stimulus frequency and stimulus duration (short or long) was manipulated within subjects and stimulus spacing (narrow or wide) between subjects. The exposure time conditions were blocked and counterbalanced across participants. Each of the 8 stimulus frequencies were presented 50 times each, resulting in 400 trials per condition. Participants were assigned to each condition at random, with the constraint that there were an equal number of participants in each condition.

Procedure. Participants were tested individually in a quiet room. Before each of the different exposure conditions, participants were played each of the 8 stimuli from 1 through 8. When each tone was played, a number was presented onscreen indicating which number the stimulus was assigned. Participants then completed 400 trials. The ordering of the tones within these 400 trials was completely randomised. Each set of 400 trials lasted approximately 20 minutes. Participants were given the opportunity to take a short break every 100 trials.

A typical trial proceeded as follows. A fixation mark ‘?’ was presented at the centre of the screen to indicate that a trial was commencing. After 300 ms, a tone then sounded. In the standard exposure condition, this tone lasted for 500 ms or until a response was made. In the long exposure condition, this tone lasted for 30 s or until a response was made. Once a response was made, there was a brief pause of 50 ms before the correct response was presented in the middle of the screen for 500 ms. Between each trial there was a silent pause of 1,000 ms before the next trial began. Participants were instructed to respond as quickly and as accurately as possible.

The Experiment had ethical approval from the relevant institutional ethics committee.

Results and Discussion

Trials were excluded from the analysis if their RTs were longer than 3,000 ms or shorter than 150 ms. This led to the removal of 3.44% of trials from analysis. Figure 1 shows mean proportion correct and mean RT for each stimulus for the narrow and wide spacing conditions and the short and long duration conditions. The diagnostic pattern predicted by the EGCM is a reduced bow effect in RT for the short duration condition (although this could also affect the bow effect in accuracy). The reduced bow is predicted because the EGCM operates by extending the time available for perceptual processing in order to increase certainty in responding for stimuli that are more similar to the other stimuli in the set (i.e. the stimuli in the middle of the range). This has little effect on accuracy, because of a diminishing return on additional information accumulated, but extends RT, producing the bow effect in RT. Figure 1 panels A and B show that clear bow effects in RT were observed (faster responding of stimuli toward the end of the range) but that the magnitude of the bows were similar for the short and long duration conditions. An 8 (stimulus frequency) x 2 (short or long duration) x 2 (narrow or wide spacing) mixed ANOVA was performed on mean RT with stimulus and duration as within-subject variables and spacing as a between-subject variable. The ANOVA yielded a significant effect of stimulus only *F*(7, 434) = 32.64, *MSE* =87858.85, η_p^2= .35, *p* < .001 (Greenhouse Geisser corrected). There was therefore no evidence for a modulation of the bow effect across durations conditions, with the interaction between stimulus and duration not significant. *F*(7, 434) = 0.874, *MSE* =12021.18, η_p^2= .014, *p* = .51 (Greenhouse Geisser corrected).

Response accuracy also showed a clear bow effect in all conditions with more accurate responding for stimuli toward the ends of the stimulus range. Within each spacing condition the observed bows for the different duration conditions were very similar. The only apparent difference was a slight increase in response accuracy at the ends of the stimulus range in the long duration condition. An 8 (stimulus frequency) x 2 (short or long duration) x 2 (narrow or wide spacing) mixed ANOVA was performed on mean proportion correct with stimulus and duration as within-subject variables and spacing as a between-subject variable. The ANOVA yielded a main effect of stimulus, *F*(7, 434) = 120.97, *MSE* =.04, η_p^2= .66 *p* < .001, and a significant interaction between stimulus and duration, *F*(7, 434) = 2.41, *MSE* =.006, η_p^2= .37, *p* = .037 (Greenhouse Geisser corrected). This interaction between stimulus and duration in accuracy alone was unexpected. In the long duration condition stimuli towards the end of the range were responded to more accurately without any additional time taken to respond. This is not what would be predicted by the EGCM-RT, where a small change in accuracy should be reflected in a larger change in RT. It is not immediately obvious why duration would impact accuracy without a concurrent change in RT. It may be that in the long exposure condition the stimulus remaining audible slightly increased participants' confidence in making responses toward the ends of the ranges, which in turn would increase response accuracy for these stimuli. Regardless, the result is clearly contrary to the prediction of the EGCM-RT.

The central finding was therefore that the predicted reduction in the depth of the RT bow in the short duration condition was not evident. Why was this the case? Response times for all stimuli were longer than 1,100 ms and, according to the EGCM-RT (Kent & Lamberts, 2005, 2016), this time is spent on perceptual processing, non-perceptual processing, and response production. In the short duration condition, fixing the stimulus duration at 500 ms meant that there was only 500 ms of perceptual processing time (although some limited sampling of an echoic memory trace could occur after this point). According to the EGCM-RT this should limit the magnitude (the difference in RT between the end and middle stimuli) of the RT bow effect in this condition to less than 500 ms. The RT bow effects in the short and long duration conditions would therefore differ only if more than 500 ms was required for stimulus sampling in the long duration condition. Within the framework of the EGCM-RT the identical RT bow effects in the two duration conditions therefore suggests that less than 500 ms was required for perceptual processing. Although feasible, this is problematic for the EGCM-RT as it leaves more than half of the total RT unexplained, or, more accurately, the EGCM-RT can only explain the results by assuming a large amount of time for non-perceptual processing or response production, which runs counter to a model that stresses the importance of perceptual processing. Moreover, this differs considerably from Kent and Lamberts (2005, 2016) applications of the EGCM-RT to absolute identification in which the time for non-perceptual processing and response production was set to be 250 ms, a small proportion of the overall RT. It seems then that the current data present a challenge to the EGCM-RT.

One potential problem with Experiment 1 is that, as masking was not used, it could be argued that perceptual processing continues from a perceptual representation (e.g., echoic memory) that outlasts the 500 ms stimulus duration. However, it is unlikely that this would account for the majority of the remainder of the RT given previous studies (e.g. Guest, Kent, & Adelman, 2010; Hsieh & Saberi, 2007) have typically found asymptotic performance after around 100 ms of stimulus exposure with masking. To address this concern, in Experiment 2, we adopted a slightly different approach. Six stimulus durations were used that ranged from 10 ms to 300 ms and stimuli were pre- and post-masked. The more nuanced manipulation of stimulus duration meant that we could produce clear performance differences across different stimulus durations enabling a more robust test of the EGCM-RTs predictions that reduced RT bow effects should be observed for short stimulus durations. In addition, systematically manipulating stimulus duration produces a time course of accuracy function that can be modelled in order to provide accurate estimates of perceptual processing rates, which is not possible when a respond-when-ready task is used (Kent & Lamberts, 2005, 2016). The EGCM-RT was then adapted and fit to this data. In addition to manipulations of exposure duration we also included a stimulus spacing manipulation and a set size manipulation. For modelling purposes, it is important to manipulate standard variables so that the model can be shown to account for standard effects as well as new effects. This reduces the danger that a model produces unrealistic parameter sets that account for new patterns of data, but do not account for standard effects. This is particularly the case when such effects may depend on similar mechanisms. Manipulations of exposure duration, stimulus spacing and set size therefore provided a comprehensive set of data for formal modelling. Because averaging across individuals can introduce artefacts into the averaged data and because it is important that models can account for individual data patterns, we intensively tested three participants and evaluated model predictions against each participant's data.

Experiment 2

Method

Participants. Two female and one male participant, all research staff from a British university, were paid £8 (approximately $13) per hour to participate.

Materials. A Pentium II computer was used for stimulus presentation and response registration. Participants sat 160 cm from the center of a 43.2 cm CRT monitor set at resolution of 800 x 600 pixels with a refresh rate of 60 Hz. Stimuli were presented in stereo over Plantronics Hi-Fi Audio 90 headphones. Responses were made via a custom-made button box connected to the computer's parallel port (allowing millisecond accuracy in response timing). There were 13 buttons on the button box, 12 black buttons equally spaced in a semi-circle around a single red button.

Stimuli. The same two sets of tone pitches as Experiment 1 were used, but each tone was pre-masked and post-masked with white noise chosen randomly from a set of 10 samples of white noise that had higher average amplitude than the stimuli.

Stimuli in the wide spacing condition were labelled 1-8 and stimuli in the narrow condition were labelled 11-18. This was intended to reduce any confusion generated by two tones having the same response label. On the button box the central eight stimuli were labelled 1-8 or 11-18 depending on the stimulus spacing. Thus although the same response buttons were used in the wide and narrow conditions, the buttons were labelled differently. Within each spacing condition, each stimulus was assigned a unique response label and response button regardless of whether *N* = 6 or 8. Thus when *N* = 6, the central six response options and central six stimuli were used (either 2-7 or 12-17). Response mapping was the same for all participants within each task. The smallest stimulus label referred to the lowest frequency and the largest stimulus label referred to the highest frequency.

Design. Two types of stimulus spacing (wide and narrow) and two set sizes (N = 6 and N = 8) were used. Stimuli were presented for either 10, 25, 40, 55, 100 or 300 ms. Multiple stimulus presentation times were required in order to produce an adequate time course function from which estimates of perceptual processing rates could be derived. Each level of this 6 (exposure duration) x 2 (stimulus spacing) x 6 or 8 (stimulus depending on set size) design was repeated 50 times per participant (8,400 trials in total). The experiment was composed of ten one-hour long sessions. Within each session, set size and stimulus spacing remained constant but exposure duration and stimulus frequency changed randomly. Participants completed five sessions of one stimulus spacing followed by five sessions of the other stimulus spacing. Within the five sessions of each stimulus spacing, two sessions of set size *N* = 6 were completed followed by three sessions of *N* = 8 (or vice versa). The order in which the different stimulus spacing and set size conditions were completed differed for each participant.

Procedure. At the start of each session, participants were instructed as to the mapping to use by presentation of each stimulus and its associated numerical label for 500 ms. A trial began when participants pressed the central red button with the index finger of their dominant hand. A small white cross was then presented centrally for 300 ms followed by a 300 ms blank interval, then a 200 ms mask. The stimulus was presented for the selected exposure duration, and was followed by a mask and a visual “???” response signal presented centrally, both of which continued until response.

Participants were instructed to respond as quickly as possible after the visual “???” response signal was presented and to keep the red button depressed until they were ready to make a response on a black response button (participants were asked not to make a response before presentation of the visual response signal to ensure that the full stimulus duration was utilised). Failure to adhere to these instructions (detected in the latter case by a latency from release of red button to press of black button in excess of 1,000 ms), or a latency from response signal to red button release in excess of 3,000 ms led to a relevant on-screen warning (this was to encourage participants to begin responding within 3,000 ms and to move directly to a response button). If participants depressed a black button not in use in the current session, they were instructed to try again. Once a valid response was registered, the correct response was displayed for 1,200 ms, or 3,200 ms if a warning display was shown simultaneously.

Trials were excluded from further analysis if: the red button was released too early; an invalid response was made; or if RTs (measured as the time from stimulus onset to black response button press) were longer than 3,000 ms or shorter than 400 ms. In addition to excluded trials, the first 20 trials of each session were treated as practice and not analysed. Excluded trials constituted 1.74% of the total number of non-practice trials.

The Experiment had ethical approval from the relevant institutional ethics committee.

Results and Discussion

Stimulus duration effects

Figure 2 (first row) shows proportion correct averaged across stimuli at different exposure durations. Increasing stimulus duration had a large effect on response accuracy, with generally more accurate responding at longer stimulus durations. At the shortest duration response accuracy was well above chance levels for all participants and asymptotic accuracy was reached after only 60 ms of stimulus exposure for Participant 2 (panels iii and iv) and after only 100 ms of stimulus exposure for Participants 1 (panels i and ii) and 3 (panels v and vi). Although relatively high levels of accuracy were observed at the longest stimulus duration there was a trend in some cases for the 300 ms duration to show less accuracy than the 100 ms duration. This may be an artefact of the lesser experience participants had of identifying stimuli at such a long duration.

The large effect of stimulus duration on response accuracy supports the notion that stimulus processing was interrupted by the offset of the stimulus and onset of the white noise mask. An alternative interpretation is that greater accuracy at longer stimulus durations was observed because it was more likely that a stimulus had entered auditory short term memory and so was available to be used in the decision. Data on stimulus/response confusions speak against this interpretation. At shorter stimulus durations it should be less likely that a stimulus has been encoded into auditory short term memory and so errors are more likely be random and unsystematic. In contrast, Figure 3 (which, for brevity, shows stimulus/response confusions for the shortest exposure condition when set size was 8) shows that errors were systematic at the shortest stimulus duration conditions consistent with the notion that at the shortest exposure duration some perceptual information is generally available with which to guide responses.

Set size and stimulus spacing

As is evident in Figure 2 (second row) set size had a large effect on accuracy for all participants with more accurate responding when $N = 6$ compared with $N = 8$. Similarly, stimulus spacing had a large effect for all participants with more accurate responding when stimuli were widely-spaced compared to narrowly-spaced. Figure 2 (first row) also shows that these spacing effects and set-size effects were evident even at early exposure durations.

Figure 2 (third row) shows that participants demonstrated a consistent effect of set size on RT with faster responses when $N = 6$ compared with $N = 8$. The effect of stimulus spacing on RT was, however, mixed. Participant 1 showed faster RTs for widely spaced stimuli across both set sizes (panels xiii and xiv), whereas Participants 2 and 3 displayed faster RTs for narrowly-spaced stimuli when $N = 6$ (panels xv and xvii), but faster responding for widely-spaced stimuli when $N = 8$ (panels xvi and xviii). It is possible that practice may have contributed to these different effects. Although within-subject manipulations of set size and stimulus spacing are not uncommon in absolute identification studies (e.g., Kent & Lamberts, 2005; Lacouture & Marley, 1995; Nosofsky, 1983), disentangling the effects of these manipulations from that of practice effects (Dodds, Donkin, Brown. & Heathcote, 2011; Rouder, Morey, Cowan & Pfaltz, 2004) or carryover effects is difficult. These can be ruled out as explanations for the set-size effect as this was consistent across participants who completed sessions in different orders. Determining the extent to which the inconsistent effects of stimulus spacing on RT are due to meaningful individual differences or practice is more difficult. Table 1 shows the order in which participants completed the sessions, the accuracy and RT for each session and RTs for the first and last block within a session. A clear effect of practice on accuracy was evident for Participant 1 and 3, with accuracy from the first to last session within each condition generally improving for each participant. This pattern was less consistent for Participant 2. In terms of RT, the effect of practice appeared to change between participants and conditions. Participant 2 showed a reduction in RT from first to last session for all conditions, whereas Participants 1 and 3 showed a mixture of both increases and decreases in different conditions. Even within a session practice effects on RT were not robust, except for Participant 1. Moreover, between spacing conditions, no clear practice effect was apparent. For example, Participant 2 and 3 showed faster responding for narrowly spaced stimuli when N=6 but Participant 3 completed the narrow spacing conditions first whereas Participant 2 completed the narrow spacing condition last. Clearly then, not all the individual differences observed in the effect of stimulus spacing on RT can be explained in terms of practice effects. This is particularly surprising given stimulus spacing had a consistent effect on accuracy and we return to this issue in the discussion.

Keeping stimulus spacing constant when manipulating set size introduces a range confound (the distance on the stimulus dimension between the ends of the stimulus range). It is well established that increasing range, while keeping set size fixed, lowers response accuracy (Lockhead and Hinson, 1986). Thus, it may be possible that the set size effects observed were due to range, not set size per se. Arguing against that is the observation that increasing stimulus spacing increased the range much more than the set size manipulation yet increasing stimulus spacing improved accuracy. As there could have been a trade-off between the effects of increasing stimulus spacing and increasing range, this simply tells us that the effect of range was not large enough to counter the effect of stimulus spacing. This does not seem to fully stack up with the large effect of set size on accuracy, which, if caused by range, would suggest that range had quite a large effect. However, it is impossible to say from the data whether any set size manipulation was caused by simultaneously manipulating range.

Bow effects in accuracy and RT

Assuming that shortening stimulus duration (and masking) decreases the time available for perceptual processing, the EGCM-RT makes the prediction that this will result in a shallower bow in RTs. This is because stimuli in the middle of the range have more close neighbours in psychological space and so in the EGCM-RT they have greater summed similarity to the other stimuli in the set. The result is that, as perceptual information is processed the relative evidence for a correct response grows more slowly for stimuli in the middle of the range and so the time for accumulating perceptual information is extended in order to maximise performance. By shortening the time available for accumulating perceptual information the opportunity to allocate relatively more perceptual processing time to central stimuli is reduced, leading to less of a RT difference between central and end stimuli. The predicted effect of increasing stimulus duration on the RT bow effect is dependent on the assumed relationship between stimulus duration and the time available for perceptual processing. A strict assumption is that the sensory response (from which information is sampled) that occurs when a stimulus is presented limits the total amount of information that can be extracted from the stimulus (Loftus, Busey, & Senders, 1993).

As masking should diminish the amplitude of this sensory response rapidly (see Smith & Ratcliff, 2009) the actual sensory response triggered by a stimulus presentation could provide an approximation of the time available for sampling of stimulus information during perceptual processing, albeit that there will be some delay from stimulus onset to the point at which the sensory response triggered by the stimulus can be sampled. Under this assumption, the EGCM-RT predicts that the greatest magnitude of bow effect in RT (the difference in RT between stimuli at the ends of the range and those in the middle of the range) must be less than the total time available for accumulation of perceptual information.

Figure 2 shows bow effects at three stimulus durations for each participant for response accuracy (fourth row) and RT (fifth row). Data are shown for set size $N = 6$ and $N = 8$ and are averaged over spacing condition for clarity. Typical accuracy bow effects were found for all participants, even at the shortest stimulus duration. In RT, typical bow effects were also observed, although the extent of it differed markedly between participants. Critically, the pattern of RT bows at the shortest stimulus duration appears to be no different from the pattern of RT bows for longer stimulus durations. This contrasts greatly with the predictions of the EGCM-RT. Indeed, even under a more flexible assumption relating stimulus duration to perceptual processing time some differences in RT bows would be expected at different stimulus durations. In the following section, we fit the EGCM-RT and examine the extent to which it can capture the data. We then explore how changing the assumptions regarding perceptual processing may allow the model to account for the qualitative patterns in the data.

Modelling

We describe the EGCM-RT as it is applied to absolute identification (Kent & Lamberts, 2005, 2016) and detail its application to limited duration stimuli (Lamberts, 2000, gives a full description of the general model). In absolute identification, each stimulus is made up of a continuously valued dimension, in the model it is assumed that the relevant psychological dimension is composed of discrete information elements that are sampled without replacement. For computational tractability, we assume a finite number of elements (4 in our application here, in order to maximize model fit, while achieving parameter optimisation in a reasonable amount of time) but in reality it can be assumed that very many samples of information may be abstracted from a stimulus and accumulated (see Kent et al. 2014 for more discussion on the stimulus sampling assumption). As information is sampled the psychological representation of the stimulus becomes more differentiated in psychological space. As per Kent and Lamberts (2005) a decreasing rate of information gain for each additional element sampled was used in order to account for the set-size effect in both RT and accuracy. Stimulus sampling is a probabilistic process, with the probability of an element, *i*, being sampled at or before time *t* with a stimulus duration of *T*:

$$P(\Phi(i)=1\,|\,t;T)=1-\exp(-q\min(t,T)), \tag{1}$$

where $\Phi(i)$ is 1 if element *i* has been sampled, and 0 if not; *q* is the rate at which elements are accumulated from the stimulus (if *q* is large, processing is fast). Sampling stops if all elements have been sampled or if the stimulus is masked.

As elements are sampled, the evidence for each response is evaluated by comparing the similarity of the current stimulus representation to exemplars held in memory. The representation of exemplars in memory in the EGCM-RT is based on the concept of multidimensional space as embodied initially by the Generalised Context Model (Nosofsky, 1986). The similarity between stimulus *j* and stored representation *k*, η_{jk}, is dependent on the number of sampled elements at time *t*, φ_t:

$$\eta_{jk}(\varphi_t) = \exp(-c_S(1-\lambda^{\phi_t})d_{jk}), \qquad (2)$$

in which c_S is the discriminability index (which depends on spacing *S*), we assume an exponential psychological distance between values of *j* and *k* (d_{jk}). Here *j* and *k* refer to stimulus labels as stimuli are equally spaced on the psychological scale. Following Kent and Lamberts (2005), λ is a diminishing-information-returns constant (the influence of each element decreases as a power function of the number of sampled elements φ_t).

As the similarity between the current stimulus *k* and the stored exemplars for one response *j* increases, the likelihood of sampling stopping and responding increases. If all elements have been sampled, or the stimulus offsets (at time *T*), sampling stops, otherwise, the probability of stopping sampling after φ_t elements have been sampled is given by the relative evidence for one response alternative *j* compared to all alternatives:

$$P(Stop \mid j, \varphi_t) = \frac{\sum_{k=1}^{N}[\eta_{jk}(\varphi_t)]^{\theta}}{(\sum_{k=1}^{N}\eta_{jk}(\varphi_t))^{\theta}}, \qquad (3)$$

In which the parameter θ (≥ 1) indexes the degree to which equivocal evidence will lead to further sampling. At $\theta = 1$, stopping occurs at the first time of asking (when the first element is perceived). As θ gets bigger, stopping becomes less probable and more contingent on one exemplar having much higher similarity to the stimulus than the other exemplars. N is the number of response alternatives. Overall, this rule indicates how the stopping probability depends on the relative evidence for the response alternatives. For example, if the presented stimulus is highly similar to one exemplar but not others, then there is a high probability that sampling will stop early. When sampling has stopped the probability of giving response k, R_k, is equal to:

$$P(R_k \mid j, \varphi_t) = \frac{\eta_{jk}(\varphi_t)^{\theta}}{\sum_{k=1}^{N} \eta_{jk}(\varphi_t)^{\theta}}, \tag{4}$$

in which θ affects the choice probability with larger values of θ leading to more deterministic responding. Equations 3 and 4 are related such that the more the response selection rule (Equation 4) favors a particular response, the more likely the stopping rule (Equation 3) will permit the response selection rule to be invoked. This means that hard-to-identify stimuli are responded to relatively slowly, because they require additional stimulus sampling, especially when additional sampling is relatively ineffectual (λ is high). Finally, to predict a RT, a residual time parameter, t_{res}, is added to the time at which a response is selected. The residual time reflects lag in the system, non-perceptual processing time and the time to execute a physical response.

The EGCM-RT predicts bow effects in accuracy because as stimuli get closer to the ends of the range they become more isolated (in terms of psychological distance, with fewer near neighbours) compared to central stimuli and so responding is more accurate. This also results in stimuli towards the end of the range requiring less evidence to be accumulated before an accurate response can be given, generating a bow in RTs. Set size effects in accuracy are predicted from the choice rule (Eq. 4) as in smaller set sizes each stimulus is relatively more isolated. This also leads to faster responding as less evidence is required in order to make accurate responses in smaller set sizes.

To assess the model predictions, the EGCM-RT was fitted to the choice proportions and mean RTs from each participant individually. In order to fit the model to the data, we calculated the sums of squared differences between the model predictions and the data for both choice proportions (the full stimulus-response confusion matrix) and mean RTs for each stimulus. In order to simultaneously fit both choice and RT data we combined the sums of squares, but because RTs and proportion are on different scales, it was necessary to divide each RT sums of squares by the variance associated with that RT in the data. Parameters were selected using a Simplex algorithm (Nelder & Mead, 1965) which minimised the combined sums of squares.

In the model development, we developed and tested nine model versions. For brevity, we report the two most important versions here and provide a step by step outline of the nine model iterations run and their respective fits in an online supplement. Each of these models was run in order to test differing hypotheses. Out of these there were three classes of models. The first of these was the standard EGCM-RT as outlined above whereby the time for perceptual processing was assumed equivalent to stimulus duration. The second model relaxed this assumption and enabled the time for perceptual processing to outlast the stimulus. Thus, a parameter was estimated for the time for perceptual processing at each stimulus duration with the restriction that the perceptual processing time for one stimulus duration could not be greater than that of a longer stimulus duration. To precis, neither of these models was able to capture key elements of the data. The final model therefore incorporated both a perceptual sampling process and a similar memory sampling process. Importantly, sampling from memory can continue after stimulus offset. This model provided a much better fit of the data. We now explore in depth two of these models, the best performing version of the standard model and the final best fitting model in order to elucidate the reasons why the standard model (and versions of it) could not capture particular trends in the data. Models in between these two are fully explained and explored in the online supplementary material.

In the initial class of models, the time for perceptual processing was assumed equivalent to stimulus duration. Modelling analysis revealed that spacing effects were best captured by allowing the discrimination constant (c) to vary with spacing (the rationale being that discriminability is better for more widely space stimuli) rather than response determinism (θ). In order to capture the full extent of set-size effects in accuracy (these are in part captured by the choice rule in Eq 4), Kent and Lamberts (2005) showed that it was necessary to allow both θ and c to vary across set-sizes (without the assumption of diminishing returns; a similar assumption was followed by Karpiuk, Lacouture, & Marley, 1997, in their accumulator model by allowing the response criterion to vary by set size). Here, allowing c to vary by set size, captured the set size effect (in accuracy) best, with c decreasing with larger set sizes (indicating lower discriminability). As increasing set size also increased stimulus range and increasing stimulus range is known to decrease accuracy (Lockhead & Hinson, 1986), the decrease in c with increasing set size may also allow the model to capture part of the range effect, although note that the model is not able to capture the range effect without allowing c to vary with range. Fits of a version of the model (the EGCM-RT-

c) with c varying for spacing and set size are shown in Figure 2 (see Table 2 for fit and parameter values). This model had eight free parameters: t_{res} (residual time); c_{n6} , c_{n8}, c_{w6}, and c_{w8} (discrimination constants for the four spacing and set size conditions produced by the 2 x 2 manipulation); q_p (the processing rate for perceptual information elements); λ (the base of the diminishing return function); and θ (response determinism). In this standard model, the stimulus sampling time was assumed to be equivalent to the stimulus duration. The model successfully accounted for the bow effects in accuracy, higher accuracy for widely spaced stimuli compared to narrowly spaced stimuli, higher accuracy for set size six relative to set size eight and predicted the increase in accuracy with stimulus exposure duration. Significantly, and as expected, the model failed to capture a central aspect of the data, the dependency of RT on stimulus (the bow effect) for all durations (see Figure 2, rows 3 and 5).

To address whether this model was critically constrained by the strict assumption equating perceptual processing time to stimulus duration we fit a model with a more flexible assumption, in which the time available for processing at each stimulus duration was allowed to vary, with the restriction that longer stimulus durations had to have longer time for perceptual processing than shorter durations. Details of this model are provided in the online supplementary material. Crucially however, by assuming long perceptual processing times the model could capture RT bows at small stimulus durations for one participant, however it could not simultaneously capture the pattern of increasing accuracy as stimulus duration increased. Relaxing the assumption that perceptual processing time was equivalent to stimulus duration therefore gave the model the flexibility to have long perceptual processing times and thus create RT bow effects. At the same time, the steepness in the rate at which accuracy increased as stimulus duration increased can only be captured by assuming relatively fast perceptual processing. Thus the model could predict either RT bows or the pattern of accuracy increasing with increases in stimulus duration, but not both simultaneously.

Overall then, variants of the standard EGCM-RT failed to produce large bow effects in RT because according to the model all the systematic variability in RTs is due to the stimulus sampling stage and thus the size of the RT bow is limited to the length of this stimulus sampling. For the model to capture above chance performance for the shortest stimulus duration and a sharp rise in accuracy for the next longest stimulus duration it has to assume information is accumulated very rapidly, i.e., a high perceptual processing rate, q_p. This leads to a short overall stimulus sampling time, preventing the model producing sizeable bows in RT. Rather, t_{res} is large as it needs to account for the majority of the RT.

A more substantial change to the EGCM-RT would be to include a more detailed memory sampling process alongside perceptual sampling. Previous findings have suggested that a process similar to perceptual sampling may also occur for memory, in which features are retrieved from memory in an analogous manner to perception (Kent & Lamberts, 2006a, 2006b, 2008; Lamberts & Kent, 2008; see Kent et al, 2014 for a review). It is possible that the EGCM-RT's ability to model choice and RT patterns in unlimited stimulus duration absolute identification (Kent & Lamberts, 2005; 2016) is a result of the model mimicking a slow memory retrieval stage and not the fast perception stage. To examine this, we combined the two processes in a new single model, the Perception and Memory Extended Generalized Context Model for Response Times (PMEGCM-RT).

In the PMEGCM-RT, the assumptions regarding perceptual element sampling are unchanged from the standard model. However, in parallel and independent to perceptual sampling, an analogous memory element sampling process also takes place. Each perceptual element is paired with a corresponding memory element. These elements are sampled in parallel, but a given element must be both perceptually sampled and sampled from memory (not necessarily in that order) for it to enter the similarity calculation. In other words, memory is sampled for relevant information that discriminates exemplars along the specific dimension. Unlike other models (e.g., Nosofsky, 1997) this means that it is not specific exemplars that are retrieved from memory but information about the psychological space (similar to the rehearsal component of Brown et al.’s, 2008, SAMBA). Only when this same information is sampled from memory and sampled from the stimulus is that information used in the similarity calculation. Thus sampling an element from the percept and from memory is required in order to link the percept with the stored knowledge of the composition of the psychological space. The rate at which memory elements are sampled is determined by q_m (analogous to q_p), such that element i independently has a probability of being retrieved at or before time t:

$$P(\Phi_m(i)=1\,|\,t)=1-\exp(-q_m t), \tag{5}$$

where $\Phi_m(i)$ is 1 if the element has been retrieved, and 0 if not. Note that, unlike perceptual sampling, sampling of memory elements can continue after the stimulus has been masked. The information available from perceptual and memory sampling at time t depends on the number of matching elements:

$$\varphi_t=\sum\nolimits_{i=1}^{n}\Phi_p(i)\Phi_m(i)\,. \tag{6}$$

Processing continues as in the standard EGCM-RT based on the value of φ_t. The PMEGCM-RT adds only one additional free parameter, q_m, to the standard EGCM-RT.

As with the EGCM-RT, model analysis showed that varying *c* for set size and spacing enabled it to capture spacing and set size effects. We therefore allowed *c* to vary in the PMEGCM-RT-*c* model. The best fitting parameters are given in Table 2 and the fits to the data can be seen in Figure 4. The model captured the set size effect well and fit the data quantitatively better than any other version of the EGCM-RT (see the online supplementary material for an overview of the nine model variants tested). Critically, it also predicted the main qualitative trends in the data including bow effects in RT for all 3 participants (Figure 4, row 3 and 5) and, except for Participant 1, the effect of stimulus duration on accuracy. Generally other predictions were good, with perhaps the exception of the effects of stimulus type on accuracy at small durations, as the data here displayed less consistent bows. The PMEGCM-RT-*c* was able to capture the bow effect in RT due to a combination of assuming that memory sampling was slower than perceptual sampling and assuming smaller θs compared to the EGCM-RT. Smaller θs indicate less deterministic responding and thus allow more opportunity for sampling. The slower memory sampling process means that it takes time to fully match the contents of the perceptual representation with that in memory, enabling the model to capture the RT bow effects. In sum, it appears that the bow effect that is observed in RT during absolute identification is not purely the result of perceptual processes but also arises in large part from another source, such as memory sampling processes or decision making processes.

General Discussion

The purpose of the two experiments reported was to test a key prediction of the EGCM-RT as applied to absolute identification (Kent & Lamberts, 2005, 2016). The EGCM-RT predicts that reducing the time available for perceptual processing should curtail the extent of the bow effect observed in RT in which stimuli toward the ends of the range are responded to quicker. According to the EGCM-RT, when the opportunity for perceptual processing is limited (at short stimulus durations) bow effects in RT will be less prominent because there is little opportunity to extend the time for perceptual processing for stimuli at the centre of the range. These stimuli are harder to identify because they have more close neighbours and the EGCM-RT normally assumes that this results in more perceptual information being accumulated for these stimuli (lengthening RT) in order to increase certainty in the response. To investigate this, Experiment 1 manipulated whether a stimulus was presented until response (long duration) or for 500 ms only (short duration). There was no evidence of RT bows being curtailed in the short condition. The only way the EGCM-RT could account for this is by assuming either that perceptual processing outlasted the stimulus duration or that perceptual processing was completed within 500 ms. If the latter was true, then this would indicate that in these experiments the majority of the RT was due to non-perceptual processing and response production, which runs counter to previous applications of the EGCM-RT in which the time course of perceptual processing appeared to explain a large amount of variability in performance across several different tasks (Lamberts, 1998, 2000; Guest & Lamberts, 2010, 2011; Kent & Lamberts, 2005, 2006b, 2016, for a review see Kent et al., 2014).

In Experiment 2, we collected extensive individual participant data on the time course of absolute identification by manipulating stimulus duration. Unlike other absolute identification studies in which stimulus duration has been manipulated

(Garner & Creelman, 1964, Pollack [cited in Miller, 1956]; Ward, 1991) the current study measured both response choice and RT and reported these measures for all stimuli. In addition to stimulus duration, both set size and stimulus spacing were also manipulated, in order to yield a rich data set for modelling purposes. We found no evidence for reduced bow effects in RT at shorter exposure durations. Rather, bow effects in RT were similar at all stimulus durations. Fitting the EGCM-RT to the data demonstrated that although the EGCM-RT was able to capture many phenomena in the accuracy data, including the effects of stimulus duration, bow effects, and stimulus spacing effects, it could not simultaneously capture bow effects in RTs and rising accuracy with increasing stimulus duration.

The inability of the EGCM-RT to capture the RT bow effect at any duration suggests that this trend is not solely caused by perceptual processes. This is consistent with a number of models of absolute identification that place relatively more emphasis on response selection processes (e.g., Brown et al., 2008; Nosofsky, 1997). Critically, however, those models do not capture the increase in accuracy over stimulus duration without additional assumptions. In order to account for these data, we developed the PMEGCM-RT, which includes an information retrieval process analogous to the stochastic sampling process in perception. This model follows from previous work linking perceptual feature sampling and feature retrieval (Kent & Lamberts, 2006a, 2006b, and Lamberts & Kent, 2008). The addition of the memory sampling stage introduced only one additional free parameter, but crucially allowed the model to account for the RT bow effects at all stimulus durations. The decoupling of the perception and memory stages in the PMEGCM-RT means that perceptual sampling can occur rapidly and thus account for the effects of stimulus duration on accuracy. In contrast, memory sampling can be a slower process that can be extended for hard-to-identify stimuli, such as those in the centre of the stimulus range, thus producing a bow effect in RT.

By virtue of adding in a memory sampling process, the PMEGCM-RT was able to capture a variety of standard effects in absolute identification including the effects of stimulus duration. However, although memory sampling is involved in response selection, the PMEGCM-RT still differs from other models of absolute identification that focus on the dynamics of the response selection processes. In the PMEGCM-RT sampling from both perception and memory will continue until enough information has been sampled to make a response with a parameter (θ) determining the amount of evidence required to make a response. In this sense, there is a sampling process for response selection. In the original EGCM-RT, this was based on perceptual sampling alone and thus differed considerably from other response selection models such as the EBRW (Nosofsky, 1997; Nosofsky & Palmeri, 1997) and SAMBA (Brown et al., 2008; a detailed description of SAMBA is provided in the online supplementary material). In the PMEGCM-RT the additional memory sampling process means that response selection is based on both sampling from perception *and* from memory making it more similar to models focusing on the dynamics of response selection. Indeed, the memory sampling in the PMEGCM-RT bears some similarity with the rehearsal stage in SAMBA (based on Marley & Cook, 1984) in that both can be viewed as maintaining the experimental context, either the psychological space of previous exemplars, or the units representing the range of previous stimulus magnitudes. Importantly, in the PMEGCM-RT, the rate of processing is identical across stimuli. In contrast, in Brown et al.'s (2008) SAMBA, the response selection stage is in the form of a ballistic accumulator in which response units (one for each possible response) race to threshold with the speed determined by the response mapping strength from a short-term stimulus representation compared with a long-term stimulus representation. Likewise, in the EBRW active exemplars race to be retrieved at rates determined partly by their similarity to the stimulus. Thus clear differences between the PMEGCM-RT and the other models exist and future research will be required to exploit these subtle differences in order to better understand the task.

A central feature of the PMEGCM-RT is that it retains a perceptual sampling process that allows it to predict limited performance as a function of stimulus duration (although this version as applied to absolute identification samples a single dimension, the model has the requisite faculty for sampling independently from multiple dimensions). There is no mechanism in SAMBA linking stimulus presentation duration to accuracy. We therefore adapted SAMBA by assuming that the noise associated with the short-term psychophysical representation of the stimulus reduces as a function of time. Our analysis (detailed in the online supplementary materials) enables SAMBA to produce the stimulus exposure effect in the accuracy data, whilst predicting the other main effects reported in Experiment 2, including RT bow effects at each stimulus duration. The conclusion to be drawn from our modelling using the PMEGCM-RT and SAMBA is that, in this task, perceptual processing completes relatively quickly (probably within 100 ms) and affects early accuracy levels, whereas a slower process drives RT. Whether this process is repeated memory sampling, as in the PMEGCM-RT or a response selection process such as ballistic accumulation, as in SAMBA, will need to be examined in future research.

Another avenue for future research could be to explore the relation between accuracy and RT. The typical finding in absolute identification is that correct responses are made more quickly than errors (e.g. Kent & Lamberts, 2005; 2016).

However, the effects of stimulus spacing reported here and elsewhere (Adelman & Stewart, 2006) appear to depart from this typical relationship. Clear effects of stimulus spacing are observed in accuracy, but effects on RT are inconsistent. Spacing manipulations are by necessity between-condition manipulations, so inconsistent effects on RT could be due to criterion changes across conditions for perceived difficulty. Nevertheless such inconsistent effects on RT are problematic for models in which response accuracy and RT are linked by a common difficulty factor, for example, the similarity between stimulus representations in the EGCM-RT (Kent & Lamberts, 2005) and the EBRW (Nosofsky, 1997). In other models, such as SAMBA, RT and accuracy are less directly linked. In SAMBA the factors that affect the representation of the stimulus (its magnitude estimation) occur early on before the stimulus is mapped onto the response accumulators and the ballistic accumulation process, and it is both these latter processes that largely determine RT variability. For example, increasing the variance of the stimulus magnitudes estimated will affect accuracy through increasing the error in the stimulus magnitudes, but a) this variance is not converted into response competition (because it is sampled once per trial); b) does not make the magnitude estimates tend to be more or less central; and c) does not change the mapping solution, and these are the factors that would affect RT. Examining situations in which accuracy and RT may therefore dissociate offers a fertile ground within which to better understand response selection processes in absolute identification. For example, Donkin, Brown, Heathcote, and Marley (2009) showed that including a large spacing gap between the central stimuli or the between the end stimuli and the adjacent led to better accuracy for neighbouring stimuli, but not faster RTs for neighbours. SAMBA was able to account for this dissociation.

While showing that the PMECGM-RT provides a good account of the data presented, there are a range of other effects in the extensive absolute identification literature that we have not attempted to account for here but that other models (e.g., SAMBA) can account for including the bow effect in discriminability (as measured by *d'*), sequential effects, range effects, effects of false feedback and bias toward particular responses (for reviews, see Brown et al., 2008, Stewart et al., 2005 and more recently Donkin et al., 2015). Future work is therefore required to show how the model can capture a broader range of data than that presented here. While the model may require adaptations to account for these typical aspects of absolute identification performance, the EGCM-RT (now a special case of the PMEGCM-RT in which items in memory are fully available from stimulus onset) can account for much larger manipulations of set size, as well as RT distributions (Kent & Lamberts, 2005) and stimulus probability effects (Kent & Lamberts, 2016) which other models do not account for (Stewart et al, 2005). Perhaps more importantly, this model and its close relatives have application to other core cognitive tasks including categorization, recognition, perceptual matching, and visual search (see Kent et al., 2014, for a review) highlighting the commonality of processes in these differing tasks. Thus, this model contributes towards the goal of elucidating the underlying processes involved in core cognitive abilities, which we view as the goal of studying a task like absolute identification.

In conclusion, we have shown that in absolute identification, perceptual sampling is not the main determinant of the time course of the task. Given that the processes in absolute identification are likely to be fundamental to other cognitive tasks this suggests that perceptual processing may not be as important in many tasks as response selection. Nevertheless, there is strong evidence from perceptual categorisation to support the role of perceptual processing (e.g., Guest & Lamberts, 2011; Lamberts & Freeman, 1999). An open question is the extent to which such findings can in part be explained by a memory sampling process that mimics a perceptual sampling process (e.g., Kent & Lamberts, 2006b). Importantly in absolute identification, stimuli are very simple and so may require little time for perceptual processing. In contrast, in other tasks (e.g., categorization) where stimuli and their component features are more complex (e.g., multidimensional) much more time for perceptual processing may be required. Similarly, displays with multiple stimuli or tasks in which attentional resources are limited may also require more extensive perceptual processing (although the effects of more stimuli may also influence decision processes). The time required for memory sampling will also be influenced by factors such as the strength of representations in memory or the number of relevant items or elements to be retrieved from memory (see Kent et al., 2014). For example, in absolute identification a single stimulus is compared with multiple stimuli in memory, whereas in visual search multiple stimuli are compared with a single target representation (e.g., Guest & Lamberts, 2011). These different perceptual and memory demands may influence the reliance on perceptual and memory sampling and a key area for future research is understanding such trade-offs (see Ratcliff & Smith, 2010). Nevertheless, it is clear from the current findings that both perceptual and memory sampling need to be included when modelling the time course of cognition in absolute identification. Such modelling more generally may reveal, as it has here, that the time course of perceptual processing plays a lesser role than memory sampling in determining the time taken to respond in many tasks with simple perceptual stimuli. Modelling each potential process is also essential in determining the locus of different performance limitations in cognition.

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Table 1. The Order Participants Completed the Conditions in Experiment 2

Session	Condition	Accuracy	RT (ms)	Block1	Block10
P1					
1	6N	.68	1333.41	1598.23	1327.57
2	6N	.69	1394.7	1184.54	1267.57
3	8N	.63	1410.3	1407.77	1379.91
4	8N	.63	1476.8	1419.46	1462.61
5	8N	.65	1397.47	1406.14	1291.58
6	8W	.72	1284.1	1242.44	1276.54
7	8W	.75	1293.0	1280.52	1379.24
8	8W	.76	1389.7	1394.91	1458.65
9	6W	.86	1168.25	1128.73	1101.65
10	6W	.87	1141.37	1017.94	1247.82
P2					
1	6W	.68	1055.44	1108.27	1004.82
2	6W	.71	1021.79	1032.48	962.59
3	8W	.63	1179.86	1379.13	1081.06
4	8W	.61	1049.88	1021.06	995.21
5	8W	.60	1131.16	1133.31	1224.43
6	8N	.47	1198.39	1289.43	1157.05
7	8N	.49	1137.06	1181.61	1127.25
8	8N	.54	1073.81	1183.72	941.95
9	6N	.64	1016.60	1120.11	825.19
10	6N	.60	986.86	943.38	1073.56
P3					
1	8N	.54	892.19	1104.63	866.25
2	8N	.62	860.39	839.61	942.19
3	8N	.72	947.71	883.64	1023.19
4	6N	.74	695.02	737.84	746.26
5	6N	.81	766.31	729.88	765.54
6	6W	.85	747.00	767.51	747.58
7	6W	.87	786.52	734.72	798.18
8	8W	.77	847.36	842.28	818.75
9	8W	.76	839.13	905.65	833.25
10	8W	.81	820.50	806.99	794.44
Overall				1086.27	1059.96

Note. P = Participant. In the Condition column, set size is indicated by the number 6 or 8 and stimulus spacing by N (narrow) or W (wide).

Table 2. Goodness of Fit (Joint Sums of Squares) and Parameter Estimates for the EGCM-RT-C and the PMEGCM-RT-c

Model	Pp.	Fit	t_{res}	c_n		c_w		q_p	q_m	θ	λ
				c_{n6}	c_{n8}	c_{w6}	c_{w8}				
EGCM-RT-c	1	4.215	1204	0.206	0.189	0.341	0.249	0.129		8.56	0.628
	2	4.386	1015	0.649	0.505	0.795	0.687	0.124		23.29	0.978
	3	2.746	782	1.913	1.357	2.434	1.986	0.146		20.76	0.987
PMEGCM-RT-c	1	3.695	252	0.794	0.737	1.273	0.959	0.784	0.001	1.82	0.000
	2	4.338	150	0.549	0.418	0.669	0.572	0.054	0.002	2.54	0.353
	3	2.701	150	0.722	0.498	0.927	0.736	0.077	0.003	3.11	0.516

Note. Pp = Participant; subscript 6 = set size 6 and 8 = set size 8; subscript n = narrow spacing condition and w = wide spacing condition

Figures

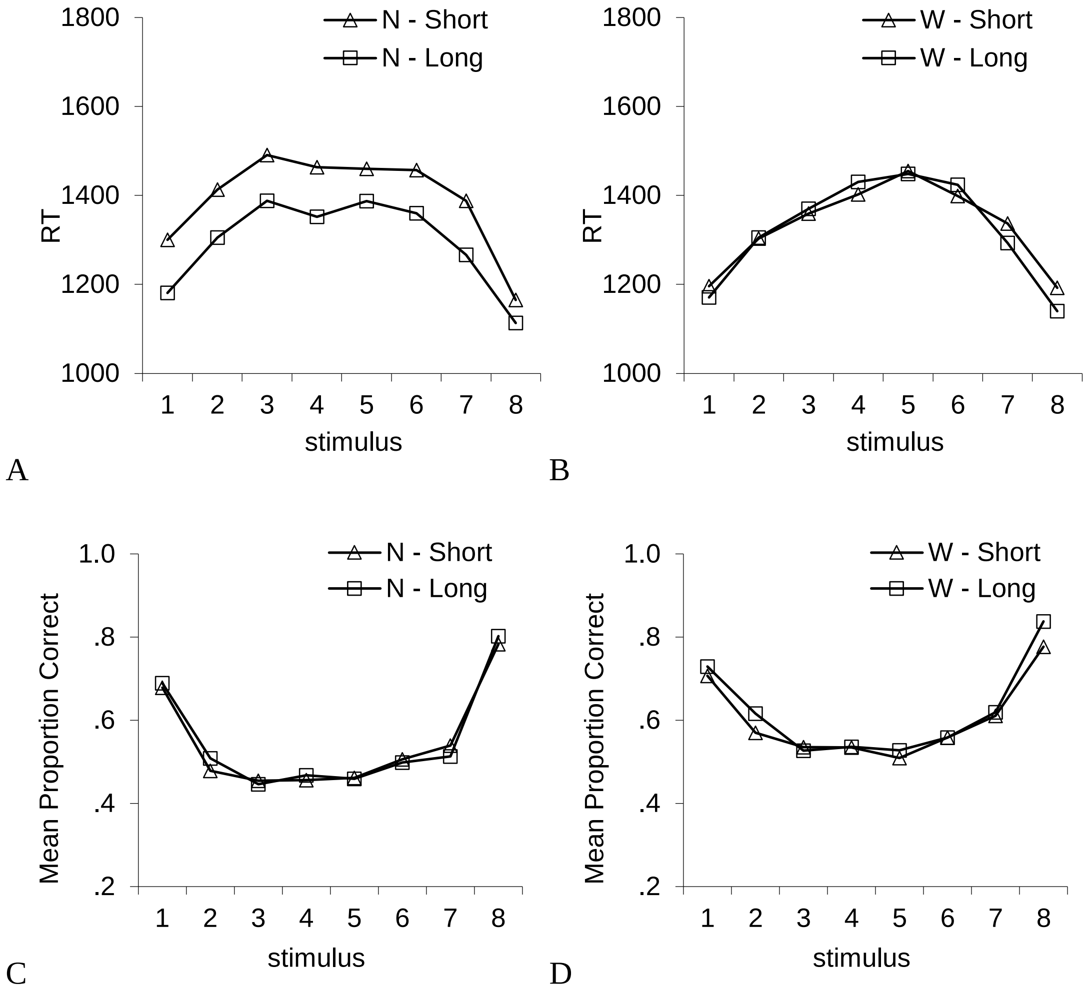

Figure 1. Mean proportion of correct responses (A-B) and mean RT (C-D) for each stimulus for the short and long duration conditions and for each type of stimulus spacing (W=wide, N=narrow).

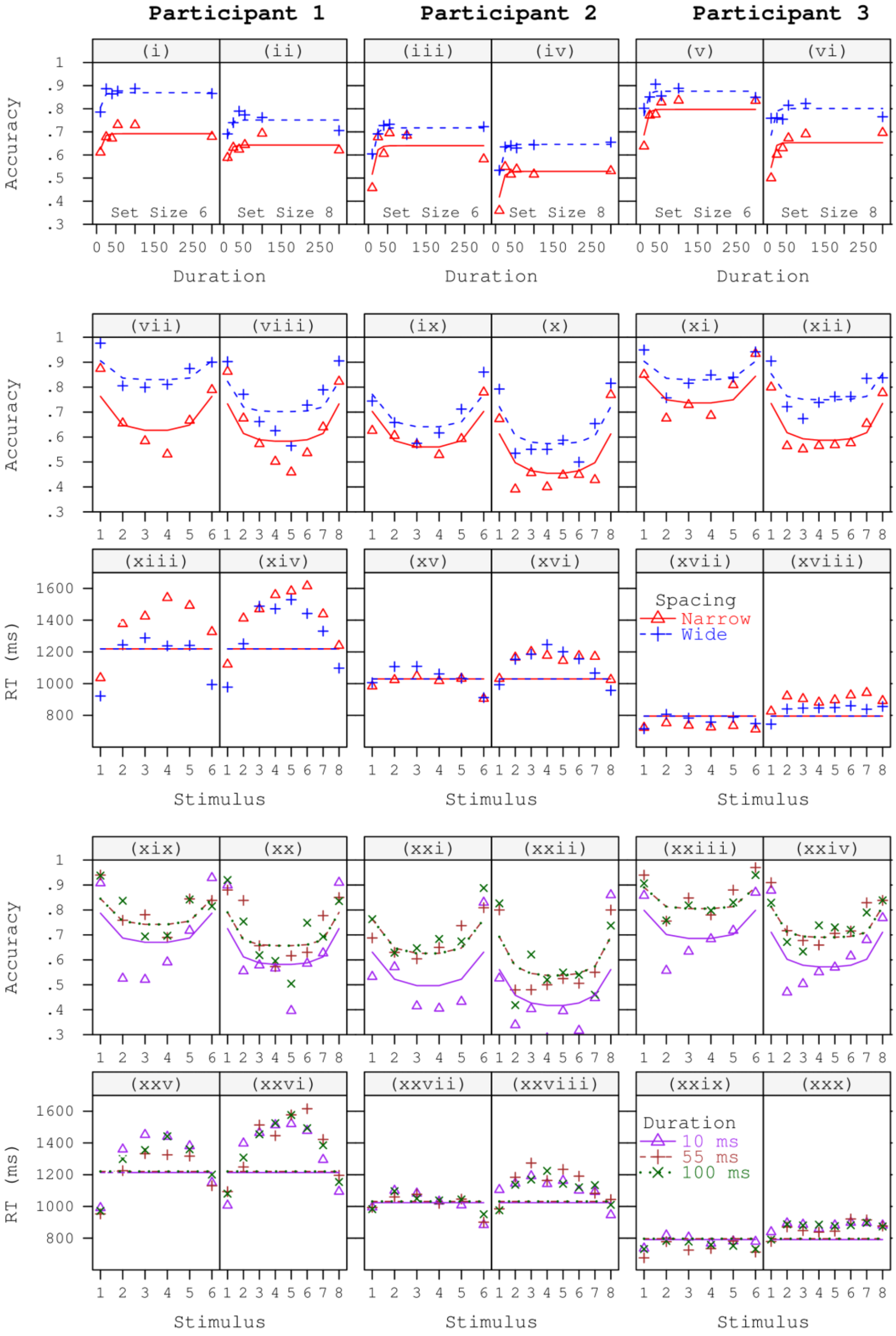
Participant 1
Participant 2
Participant 3
(i)
(ii)
(iii)
(iv)
(v)
(vi)
Set Size 6
Set Size 8
Accuracy
Duration
0 50 150 250
(vii)
(viii)
(ix)
(x)
(xi)
(xii)
(xiii)
(xiv)
(xv)
(xvi)
(xvii)
(xviii)
Spacing
Narrow
Wide
RT (ms)
Stimulus
(xix)
(xx)
(xxi)
(xxii)
(xxiii)
(xxiv)
(xxv)
(xxvi)
(xxvii)
(xxviii)
(xxix)
(xxx)
Duration
10 ms
55 ms
100 ms

Figure 2. Data (markers) for Participants 1-3 (each column shows the data from one participant). The EGCM-RT-c predictions are shown as lines. The first row shows accuracy (proportion correct) as a function of stimulus duration, for the wide stimuli (crosses) and narrow stimuli (triangles) for Set size 6 (panels i, iii, and v) and Set size 8 (panels ii, iv, and vi). Rows two and three show accuracy and response time, respectively, as a function of stimulus position, for the wide stimuli (crosses) and narrow stimuli (triangles) for Set size 6 (panels vii, ix, xi, xiii, xv, and xvii) and Set size 8 (panels viii, x, xii, xiv, xvi, and xvii); in the third row, the prediction lines are essentially identical for the two spacings. The fourth and fifth rows show accuracy and response time, respectively, as a function of stimulus position, at stimulus durations of 10 ms (triangles), 55 ms (crosses), and 100 ms (asterix), for Set Size 6 (panels xix, xxi, xxiii, xxv, xxvii, and xxix) and Set size 8 (panels xx, xxii, xxiv, xxvi, xxvii, and xxx). For the fouth row, the prediction lines are essentially the same for 55 and 100 ms. For the fifth row, the prediction lines are essentially the same for all three durations.

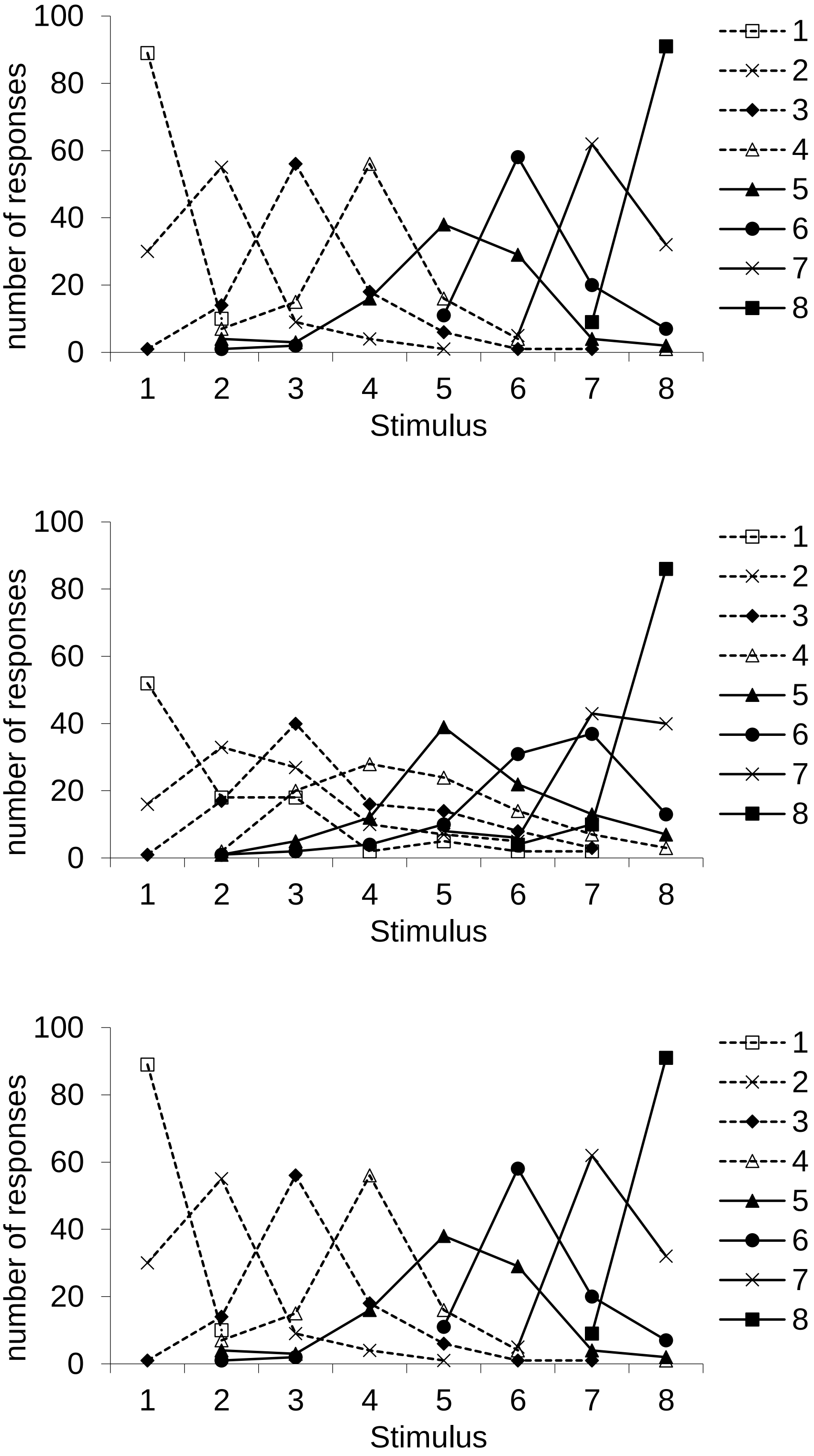

Figure 3. Stimulus-response confusion matrices at the shortest stimulus duration (10ms) for Participants 1-3 (in descending panels) for the set size 8 condition.

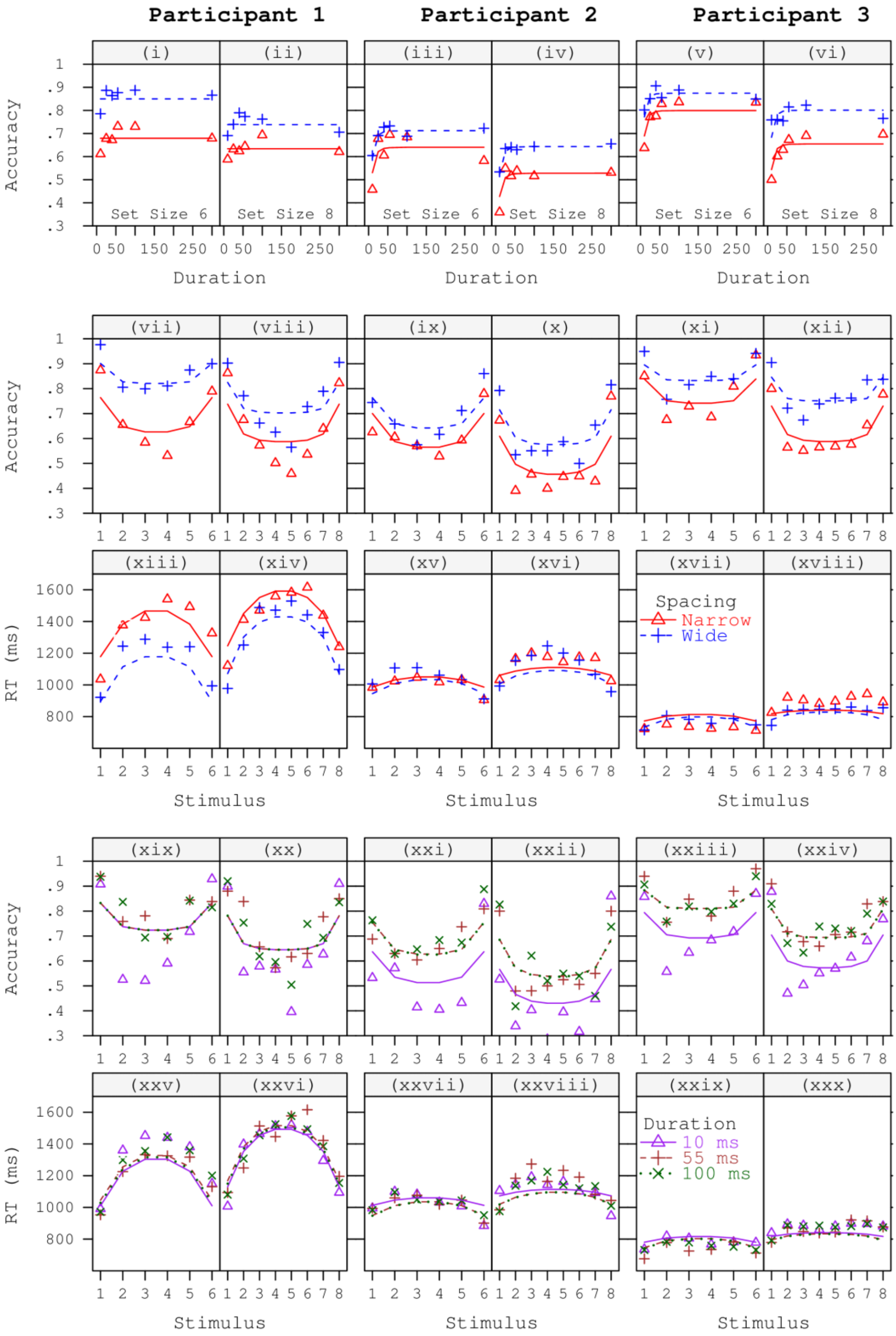

Figure 4. PMEGCM-RT-*c* predictions. Panels are as per Figure 2. The prediction lines for all three durations are nearly identical in panels (xix) and (xx). The prediction lines for 55 and 100 ms are nearly identical in panels (xxi)-(xxx)

Appendix - Online supplementary material

Modelling the *EGCM-RT*

The EGCM-RT is described in full in the paper. Here we detail the nine different iterations of the model we examined during the modelling process and consider the extent to which each model fits the data. The purpose is to provide a clear step by step guide to the decision process undertaken during modelling. Table S1 provides a summary of the model parameters.

The first model examined was the standard EGCM-RT which had six free parameters: t_{res} (basic residual time), c_n and c_w (discrimination constant for narrow and wide spacing conditions), q_p (the processing rate for perceptual information elements), λ (the base of the diminishing return function), and θ (response determinism). In this standard model, the stimulus sampling time was assumed to be equivalent to the stimulus duration. The best fitting parameters are given in Table S2 and the model predictions (for each participant) are shown in Figure S1. As expected and outlined in the paper, the model captures the bow effects in accuracy, higher accuracy for widely spaced stimuli compared to narrowly spaced stimuli, and captured the increase in accuracy with stimulus exposure duration. Significantly, the model failed to capture two important aspects of the data: The dependency of RT on stimulus (the bow effect) for all durations (see Figure S1, rows 3 and 5); and the dependency of accuracy and RT on set size (the set-size effect; see Figure S1, row 1 and row 2).

As predicted the model failed to produce large bow or set-size effects in RT because all the variability in RTs, according to the model, is due to the stimulus sampling stage. Given that the stimulus sampling stage was restricted to at most 300 ms the model could at best only produce a bow with a magnitude of 300 ms. At the same time the model is only able to capture the above chance performance for the shortest stimulus durations by assuming information is accumulated very rapidly, i.e., high q_p. This results in t_{res} having to account for the majority of the RT and thus predicted RTs are approximately equal because t_{res} is constant across stimulus position, set size, and spacing.

As outlined in the paper, in order to capture set-size effects in accuracy, Kent and Lamberts (2005) showed that it was necessary to allow both θ and c to vary across set-sizes. Our first modification of the standard EGCM-RT, EGCM-RT- θ, thus allowed θ to vary for set size 6 and 8. We reasoned that participants may have used a stricter criterion for the easier small set size (N = 6) than the more difficult larger set size (N = 8). The best fitting parameters for the EGCM-RT- θ are given in Table S2, and the fits to the data can be seen in Figure S2. As in Kent and Lamberts (2005), θ was larger for the smaller set sizes (more deterministic responding). The EGCM-RT- θ is able to capture the set size effect on accuracy (Figure S2, row 1 and 2). However, the EGCM-RT- θ still failed to account for the bow and set-size effects in RT (Figure S2, rows 3 and 5).

If the set size effect is an overall difficulty effect, and not due to a speed-accuracy tradeoff, another interpretation is that set size may impact the mapping between physical and psychological distance (an assumption common to other models, e.g., SAMBA). We therefore allowed c to vary by spacing (as in the standard EGCM-RT) and set size (as in Kent & Lamberts, 2005). The best fitting parameters of this model, the EGCM-RT-*c*, are given in Table S2, and the fits to the data can be seen in Figure S3. The quantitative and qualitative fit of the EGCM-RT-*c* and EGCM-RT- θ were very similar, with the EGCM-RT-*c* capturing the set size effect on accuracy (Figure S3, row 1 and 2) but still no RT bow or RT set size effect (Figure S3, rows 3 and 5).

Clearly, the standard model (and the modified EGCM-RT-θ and EGCM-RT-c) fails to offer a satisfactory account of the RT data. To verify this was not due to the strict interpretation of the relation between stimulus duration and perceptual processing time we relaxed this assumption such that perceptual processing time was not limited to be equal or less than the stimulus duration. This requires that some pre-perceptual auditory image is available that outlasts the sensory image and can continue to be sampled from. To instantiate this model we used a modified version of the standard EGCM-RT in which we decoupled the physical and perceptual duration of stimulus processing (the ECGM-RT-*T*). Equation. 1 in the paper was therefore replaced with:

$$P(\Phi_p(i)=1\,|\,t;T)=1-\exp(-q_p\min(t,d_T)), \tag{1}$$

with additional parameters d_{10}, d_{25}, d_{40}, d_{55}, d_{100}, and d_{300} constrained such that d_{10}, < $d_{25} < d_{40} < d_{55} < d_{100} < d_{300}$. This constraint retains a link between stimulus duration and stimulus sampling time, but also allows for a model in which there is essentially a single perceptual processing time for all stimulus durations.

The EGCM-RT-*T* parameter estimates are given in Table S2, and the fits are shown in Figure S4. This model more accurately captured the function relating accuracy to stimulus duration for Participant 2 and 3 (Figure S4, row 1) but failed to capture the effect for Participant 1 (Figure S4, row 1, first column), failed to capture the accuracy set size effect (Figure S4, rows 1 and 2), the RT bow effect for Participants 2 and 3 and the RT set size effect (Figure S4, row 3, columns 2 and 3 and row 5 columns 2 and 3). Importantly however, the model did capture the RT bow effect for Participant 1. This was because the predicted slow stimulus sampling (i.e., long perceptual durations, and relatively slow perceptual processing rates) for this participant provided the necessary time for additional stimulus sampling for hard to discriminate stimuli. However, this also meant that the function relating accuracy to stimulus duration was not produced for Participant 1, because there was time enough for a stimulus to be mostly processed for the shortest stimulus duration. In contrast, for Participant 2 and 3 the rate of perceptual processing was much faster and this was coupled with short estimated perceptual sampling durations for the first two stimulus durations, but longer estimated durations for the longer stimulus durations. This enabled the model to capture the function relating accuracy to stimulus duration but because perceptual processing was over relatively quickly, this did not enable the model to capture bow effects in RT.

Although the EGCM-RT-*T* captured some qualitative patterns in the data, it actually performed worse as a model than the EGCM-RT-*c* despite substantially more parameters. Thus, following our modifications of the standard EGCM-RT, we allowed either θ (EGCM-RT-T-θ) or c (EGCM-RT-T-c) to vary by set size in an attempt to capture the set size effects on accuracy and RT. The best fitting parameters are given in Table S2 and the fits to the data for the EGCM-RT-T-θ is shown in Figure S5 and EGCM-RT-T-c in Figure S6. Both models increase the goodness of fit by better capturing the accuracy set size effect. However, both models fail to adequately capture the bow or set size effect in RT for Participants 2 and 3 (Figure S5 and 7, row 3, columns 2 and 3) for the reasons specified above.

As specified in the main paper, we examined whether the model could better fit the data when equipped with a memory sampling process (explained in detail in the main paper). Fits for this model, the PMEGCM-RT are shown in Figure S7 and its parameters are given in Table S2. The PMEGCM-RT produces the same qualitative pattern as the standard EGCM-RT, but now also produces an RT bow effect for Participants 1 and 2 (Figure S7, row 3, columns 1 and 2), but fails to correctly produce this effect for Participant 3 (Figure S7, row 3, column 3). Importantly, although the model fails to capture the effect of stimulus duration for Participant 1 it can do this for Participant 2. This is because the model predicts a relatively fast perceptual processing rate (q_p) that captures the effect of stimulus duration, and a much slower memory sampling process (q_m) so that for more difficult choices (stimuli in the middle of the range) memory can be sampled for a longer time in order to maximise accuracy. This implies that the RT bow effects are being driven by a slower memory process. However, the model still fails to capture the set size effect on accuracy (Figure S7, rows 1 and 2).

We modified the PMEGCM-RT by allowing θ and c to vary by set size. The best fitting parameters of the models are given in Table S2 and the fits to the data can be seen for the PMEGCM-RT-θ in Figure S8 and for the PMEGCM-RT-c in Figure S9. The PMEGCM-RT-θ captured the set size effect in accuracy (Figure S8, rows 1 and 2), but did not capture the set size or bow effect in RTs for Participant 2 and 3 (Figure S8, row 3, columns 2 and 3). The PMEGCM-RT-c, however, captured the set size effect well and fit the data quantitatively better than any other model. Critically, it also captured the main qualitative trends in the data, including the bow effects in RT for all 3 participants (Figure S9, row 3 and 5) and, except for Participant 1, the effect of stimulus duration on accuracy. The reasons for this are specified in the paper.

To summarise, nine models based on the EGCM-RT were fit to the data from three participants. As expected the original EGCM-RT could not capture both a large effect of increasing stimulus duration and RT bow effects. This limitation was even apparent when relaxing the relation between stimulus duration and perceptual processing time. Augmenting the EGCM-RT with a memory sampling component (PMEGCM-RT-c) enabled the model to capture both a large effect of increasing stimulus duration and RT bow effects. This suggests that the bow effect that is observed in RT during absolute identification is not the result of perceptual processes but a memory sampling process. Interestingly, the SAMBA model of absolute identification suggests that RT bow effects are not caused by perceptual processes, instead these arise due to the dynamics of the response selection process. However in this process, there is not as much emphasis on memory sampling as in the PMEGCM-RT-c. We therefore examined the extent to which SAMBA can account for the current data.

SAMBA

The SAMBA model represents the integration of three separate models: Marley and Cook’s (1984) model of selective attention, Lacouture and Marley’s (1995) mapping process, and Brown and Heathcote’s (2005) ballistic accumulator response selection model. The model places emphasis on both short and long term memory processes (as well as allowing for relative judgements) and focuses on the decision stage as constituting the majority of RT variability. SAMBA has been shown to provide a good account for a wide range of absolute identification phenomena both in terms of choice proportions and RT distributions (e.g., Brown et al. 2008; Donkin, Brown, Heathcote, & Marley, 2009). According to SAMBA, the set of stimuli in an experiment, the context, are represented and maintained through rehearsal. Rehearsal reactivates a range of units that correspond to stimulus magnitudes. These rehearsal units are activated by a psychophysical representation, which is assumed to be relatively noiseless. Each unit does not correspond to a numerical label for that stimulus; rather, it is the summed activation of units between the psychophysical input and the ends of the current context that determines the estimated stimulus magnitude. The magnitude estimate is then transformed into *N* response strengths (based on the long-term average magnitude estimate for each of the *N* stimuli) via a mapping process that drives a ballistic accumulation process. Each of *N* response accumulators' activation is determined, in part, by the response strength (a direct result of the mapping process) and the dynamics of the accumulation process. The response given is determined by the winner of a race between the accumulators to reach a threshold. Response time is the sum of the time taken for the winner to reach threshold and a constant amount of time for non-decision processes (including perceptual processing). Thus, SAMBA, in contrast to the EGCM, identifies the decision processes, and not perceptual processing, as the mechanism responsible for the stochastic component of RTs. Brown et al (2008) also include a relative judgment component in SAMBA that we do not describe here as it is not included in our modelling as we do not address sequential effects in this study (the other predictions are not affected by the exclusion of the relative component).

Although SAMBA has been shown to provide a good account of the basic effects in accuracy and RT (the bow effect and set size effects) it does not have a mechanism to offer an account of the effects of stimulus duration on accuracy. We describe the model in more detail next and explain how it was applied to our data, including a modification to allow it to predict the effect of stimulus duration on accuracy (for a full description of SAMBA see Brown et al., 2008; we implemented SAMBA by modifying code provided by Scott Brown).

The starting point for SAMBA is a psychophysical representation of the stimulus. Each representation is spaced along a psychophysical scale (we assume equal spacing here). Brown et al. (2008) assume that in most absolute identification experiments the psychophysical representation is noiseless, as spacing between the stimuli is sufficient for perceptual errors to be negligible (in most absolute identification experiments, stimuli are pairwise discriminable, including the experiments reported here). However, a random normal variable with mean zero and standard deviation φ_p, representing psychophysical noise, is included in the model. With very short presentation durations, it is likely that there will be psychophysical noise in the representation and it is further reasonable to assume that this noise will decrease with increased stimulus exposure. Thus, in our application of SAMBA, we assume that the psychophysical representations of a stimulus starts as relatively indistinguishable and that the distribution of psychophysical representations for each stimulus becomes more peaked with increased stimulus exposure, leading to fewer errors due to psychophysical noise. This is a similar assumption (in general) to that of the EGCM-RT. Importantly, however, in our application and in the original SAMBA model, changing the amount of psychophysical noise does not affect RTs (these are determined by the response strengths and the dynamics of the ballistic accumulation process, see below). In order to predict a difference between stimulus spacing, SAMBA needs to assume that there is greater psychophysical noise (even if stimuli are pairwise discriminable).

The psychophysical representation indicates a location along the rehearsal range (following Brown et al., 2008, we assume 128 accumulating units, in order to approximate a continuum). Each accumulator in the rehearsal range is maintained throughout the experiment by selective attention, modelled as a Poisson process with a mean rate of λ events per trial. Each accumulator therefore increases with selective attention and decreases with passive decay (α), this means that from trial to trial there is variability in the activation level for each accumulator. The tradeoff between the total amount of attention and passive decay, is critical to overall identification accuracy, and is given by:

$$\eta = \lambda/(1-\alpha). \tag{2}$$

If η is low then performance is poor because there is not enough attention to maintain the set of stimuli before it decays. In order to estimate the stimulus magnitude, the activity between the psychophysical stimulus and the ends of the rehearsal range (or anchors, U for upper and L for lower) is summed and combined in a ratio to give the magnitude estimate:

$$\Sigma_L/(\Sigma_L+\Sigma_U). \tag{3}$$

This has the crucial property that variability is greatest in the middle of the range and lowest at the ends of the range, producing the bow effect in accuracy. In addition, because the process has a fixed limited capacity, it also predicts the set size effect in accuracy.

Each estimate is stored in long-term memory to build up an average representation of magnitude estimate z for each stimulus. These long-term referents are used to determine the response strength in the mapping stage. The magnitude estimates are converted into a set of N response strengths by the mapping process. The closer the magnitude estimate is to a stored representation, the stronger the response for that stimulus. Each response is assigned strength according to the following:

$$(2Y_j - 1)\, z - Y_j^2 \pm 1, \tag{4}$$

where Y_j is the average magnitude estimate for stimulus j. These response strengths are added to a common (single) sample of Gaussian noise that is added to every response strength (the noise is normally distributed with zero mean and σ_M standard deviation; representing random fluctuations due, for example, by fluctuation in arousal, similar to the drift rate from Ratcliff, 1978) and represent the rate of accumulation for each response accumulator.

The accumulators begin with activation levels determined by the previous trials and a passive decay rate. Activation decays exponentially during the inter-trial-interval, because our design (and most others) used a constant inter-trial-interval, we can subtract a constant, D, away from the activation level of each accumulator at the end of the race. During a trial, information is accumulated at a rate determined by the input response strength from the mapping process, I_j (plus the hidden noise, which affects only RT variance and not accuracy). The accumulators are subject to lateral inhibition, β (> 0), which affects the bow in RTs and the set size effect in RTs (larger N results in more inhibition). The set of accumulators' activation levels, x_j, change according to

$$\dot{x}_j(t) = I_j - \beta \sum_{p \neq j} x_p(t). \tag{5}$$

The first accumulator to reach a threshold *C* is given as the response with RT the time it takes the winning accumulator to reach threshold and a constant amount of time t_0, representing non-decision processing.

In order to estimate predictions from SAMBA we simulated 10,000 trials for each cell in the design. Table S3 gives the set of parameters we used, based upon those used by Brown et al. (2008) to fit data from Lacouture (1997), with manual changes made to each participant from the current experiment, ensuring a reasonable correspondence to the data (following Brown et al., fits were made by-eye to capture the main qualitative trends). To simulate the effect of exposure duration, we used two functions to produce a set of psychophysical noise parameters (the standard deviations of a random normal distribution) that decreased with increasing exposure duration. The first function assumed that the standard deviation of psychophysical noise was proportional to exposure time:

$$\varphi_p = k + \frac{m}{t}, \tag{6}$$

in which *k* represents psychophysical noise due to spacing (*k* = 0 in previous applications of the model and *k* = 0 for the Wide Spacing condition), *t* is exposure time, and *m* is a free parameter controlling the impact of noise due to limited viewing time. The second function we fit (suggested by Scott Brown) assumed that standard deviation of the psychophysical noise decreased exponentially with increasing stimulus duration

$$\varphi_p = k + mt^{-r}, \tag{7}$$

in which r controls the rate of decrease in noise over time (again we assumed $k = 0$ for the Wide Spacing condition). Both functions yielded almost identical noise estimates and thus produced very similar fits to the data. The standard deviations of the psychophysical noise for Equation 7 are shown in Figure S10. It is possible that the temporal decrease of psychophysical noise can be interpreted as the result of true stimulus integration before the rehearsal component of SAMBA. Nevertheless, this implementation is used to demonstrate, in principle, how SAMBA may be able to offer an account of the qualitative trends in the data, as opposed to representing a definitive model and comprehensive quantitative fit to individual participant data. Because Equation 12 represents the most parsimonious model (only 2 extra free parameters compared with the standard SAMBA model) we present fits from this model in Figure S11. With parameter values given in Table S3. We selected a symmetrical bow and in order to change the overall level of accuracy, in addition to adding psychophysical noise, we adjusted η (selective attention) and C (the decision threshold). In addition, to approximate the RT effects, we adjusted t_0 (the non-decision time constant) and D (the rate of decision decay).

Figure S11 shows that SAMBA is largely able to replicate the main effects in both accuracy and RT for all three participants. The addition of psychophysical noise, dependent on exposure duration, allowed SAMBA to produce an increase in accuracy with increased stimulus exposure (Figure S11, row 1). By allowing the narrow spacing condition to have greater psychophysical noise, SAMBA was able to predict worse accuracy for narrowly spaced stimuli than the widely spaced stimuli. SAMBA does not predict a RT difference due to spacing (Figure S11, row 3) because psychophysical noise only affects response variability and does not affect the strength of the response signal (which, in part, determines RT). SAMBA was also able to account for the set-size effect in accuracy (Figure S11, row 1 and 2) and RT (Figure S11, row 3). Critically, and unlike the original EGCM-RT, SAMBA produced a large bow effect in accuracy (Figure S11, row 4) and RT (Figure S11, row 5) even for the shortest (10 ms) duration. Because the standard deviation of the psychophysical noise decreases with increasing duration, accuracy is improved for longer durations compared with shorter durations, however, because psychophysical noise does not impact RT, SAMBA produces a bow in RTs that does not change with exposure duration. Thus, SAMBA captures all the main qualitative trends in the data, with the exception of the participant and condition dependent effect of spacing on RT. We do not see a parsimonious way to allow spacing to vary RT under the current SAMBA model. Given that the effect of spacing on RT is still poorly understood we defer for further investigation how best to implement stimulus spacing effect on RT until more data is available.

In terms of model comparisons, the fit of SAMBA and the PMEGCM-RT-c are very similar quantitatively. Qualitatively, SAMBA was able to produce an effect of stimulus duration on accuracy for Participant 1 that the PMEGCM-RT-c could not. However, it captured the set size effect less well in comparison to the PMEGCM-RT-*c*. Given that both models had similar numbers of parameters (SAMBA had 10, PMEGCM-RT-c had 9), fit the data reasonably well, and only the PMEGCM-RT-*c* predictions were quantitatively optimised, it is difficult to meaningfully compare the extent of the quantitative model fits. Moreover, the point of fitting SAMBA was to provide further evidence for the importance of response selection processes relative to perceptual processes in determining performance in absolute identification.

Table S1. Parameters of the EGCM-Family.

Symbol	Description
t_{res}	Residual time parameter, accounting for minimum takeoff time in information accumulation and motor response
q_p	Rate of information accumulation from perception
q_m	Rate of information accumulation from memory
λ	Base of diminishing returns power function in information accumulation
c	Discriminability index in similarity calculation, scales psychological distance
θ	Controls amount of deterministic responding and stopping probability
d_T	Only in EGCM-RT-T, free parameter controlling the amount stimulus sampling time

Table S2. Goodness of Fit (Joint Sums of Squares) and Parameter Estimates for All EGCM-RT-based Models

Model	Pp.	Fit	t_{res}	c_n		c_w		q_p	q_m	θ		λ						
				c_{n6}	c_{n8}	c_{w6}	c_{w8}			θ_6	θ_8		d_{10}	d_{25}	d_{40}	d_{55}	d_{100}	d_{300}
EGCM-RT	1	4.604	1204	0.2		0.287		0.131		8.44		0.631						
	2	4.679	1015	1.452		1.886		0.126		16.53		0.988						
	3	3.348	782	4.721		6.492		0.147		8.03		0.989						
EGCM-RT-θ	1	4.313	1204	0.202		0.291		0.13		9.29	7.67	0.630						
	2	4.406	1014	0.414		0.537		0.125		51.00	42.00	0.985						
	3	2.767	782	0.193		0.268		0.103		12.80	9.63	0.686						
EGCM-RT-c	1	4.215	1204	0.206	0.189	0.341	0.249	0.129		8.56		0.628						
	2	4.386	1015	0.649	0.505	0.795	0.687	0.124		23.29		0.978						
	3	2.746	782	1.913	1.357	2.434	1.986	0.146		20.76		0.987						
EGCM-RT-T	1	4.275	518	0.627		0.908		0.001		2.19		0.000	1170	1185	1235	1251	1299	1499
	2	4.661	1012	0.764		0.991		0.11		6.95		0.943	11	113	128	593	1291	1500
	3	3.335	776	0.382		0.526		0.098		6.77		0.781	12	27	468	717	798	1178
EGCM-RT-T-θ	1	4.107	507	0.616		0.894		0.001		2.41	2.11	0.000	1171	1186	1240	1255	1300	1500
	2	4.386	1009	0.342		0.444		0.09		6.72	5.54	0.821	11	68	83	756	1000	1495
	3	2.765	776	0.366		0.508		0.097		8.55	6.44	0.788	12	27	515	723	808	1156
EGCM-RT-T-c	1	4.205	1065	0.228	0.209	0.377	0.275	0.011		7.22		0.540	100	183	242	1247	1296	1499
	2	4.367	1004	1.096	0.854	1.342	1.16	0.074		10.19		0.970	16	191	207	427	472	674
	3	2.703	745	1.274	0.903	1.630	1.322	0.036		6.01		0.925	38	60	75	834	889	1097
PMEGCM-RT	1	4.088	233	0.785		1.109		1	0.001	1.76		0.000						
	2	4.773	196	0.936		1.206		0.041	4e-4	1.19		0.000						
	3	3.335	542	0.348		0.478		0.113	0.008	6.88		0.752						
PMEGCM-RT-θ	1	3.986	150	0.655		0.939		0.087	0.001	2.23	2.04	0.000						
	2	4.406	528	1.341		1.742		0.126	0.004	21.49	17.70	0.989						
	3	2.762	454	0.236		0.328		0.098	0.006	9.93	7.47	0.651						
PMEGCM-RT-c	1	3.695	252	0.794	0.737	1.273	0.959	0.784	0.001	1.82		0.000						
	2	4.338	150	0.549	0.418	0.669	0.572	0.054	0.002	2.54		0.353						
	3	2.701	150	0.722	0.498	0.927	0.736	0.077	0.003	3.11		0.516						

Note. Pp = Participant; subscript 6 = set size 6 and 8 = set size 8; subscript n = narrow spacing condition and w = wide spacing condition.

Table S3. Parameter values used to simulate SAMBA.

Parameter Description	Symbol	P1	P 2	P3
Ratio of mean number of pulses to decay rate	η	**80**	**16**	**40**
Mean proportion of activity to prior stimulus location	M	.14	.14	.14
Duration of activity to prior stimulus location	K	4	4	4
Standard deviation of noise from mapping	σ_M	.22	.22	.22
Rate of lateral inhibition	β	.03	.03	**.01**
Rate of decision accumulator decay	D	**.004**	**.004**	**.004**
Decision criterion	C	**800**	**665**	**550**
Non-decision time constant	t_0	**200**	**69**	**69**
Psychophysical noise due to spacing	k*	**0.05**	**0.05**	**0.05**
Numerator of psychophysical noise function for duration	m	**0.46**	**0.46**	**0.46**

Note. Numbers in bold reflect parameter changes from the Lacouture (1997) parameters.

*The constant for narrow spacing, for wide spacing $k = 0$; The Upper and Lower anchors were set to 1, we did not attempt to model an asymmetric bow.

Figures

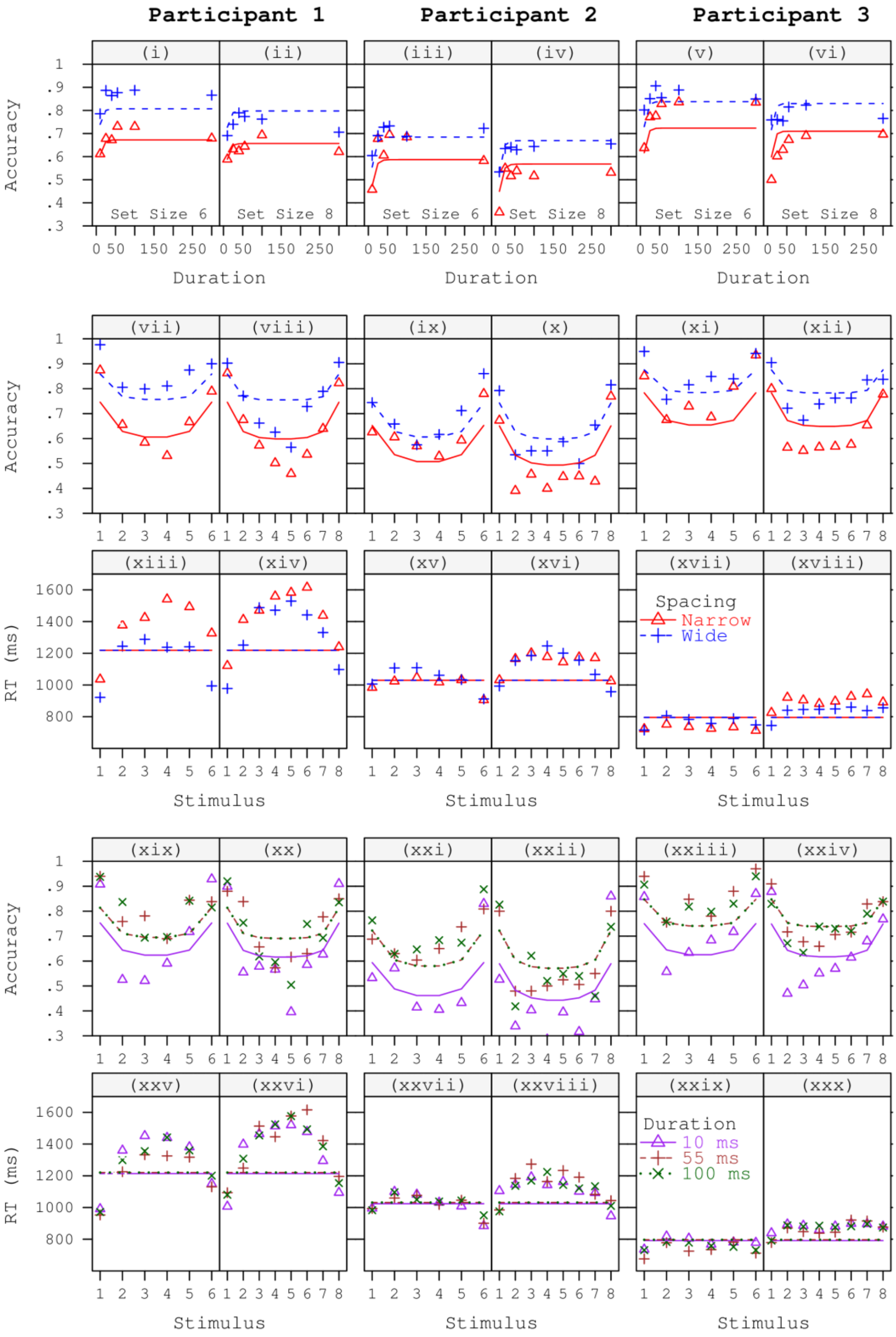

Figure S1. Data (markers) for Participants 1-3 (each column shows the data from one participant). The EGCM-RT predictions are shown as lines. The first row shows accuracy (proportion correct) as a function of stimulus duration, for the wide stimuli (crosses) and narrow stimuli (triangles) for Set size 6 (panels i, iii, and v) and Set size 8 (panels ii, iv, and vi). Rows two and three show accuracy and response time, respectively, as a function of stimulus position, for the wide stimuli (crosses) and narrow stimuli (triangles) for Set size 6 (panels vii, ix, xi, xiii, xv, and xvii) and Set size 8 (panels viii, x, xii, xiv, xvi, and xvii). The fourth and fifth rows show accuracy and response time, respectively, as a function of stimulus position, at stimulus durations of 10 ms (triangles), 55 ms (crosses), and 100 ms (asterix), for Set Size 6 (panels xix, xxi, xxiii, xxv, xxvii, and xxix) and Set size 8 (panels xx, xxii, xxiv, xxvi, xxvii, and xxx).

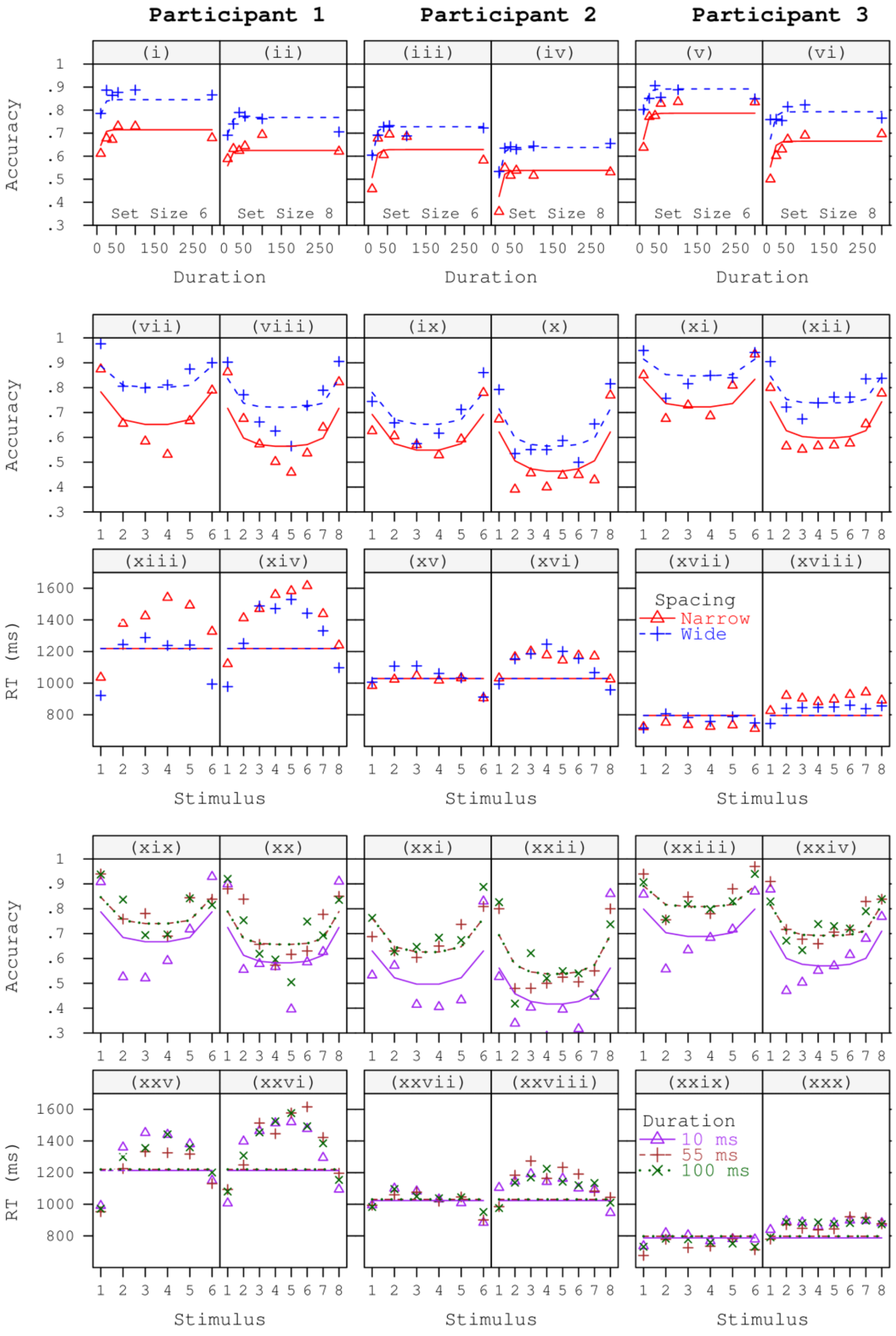

Figure S2. EGCM-RT- θ predictions. Panels are as per Figure S1.

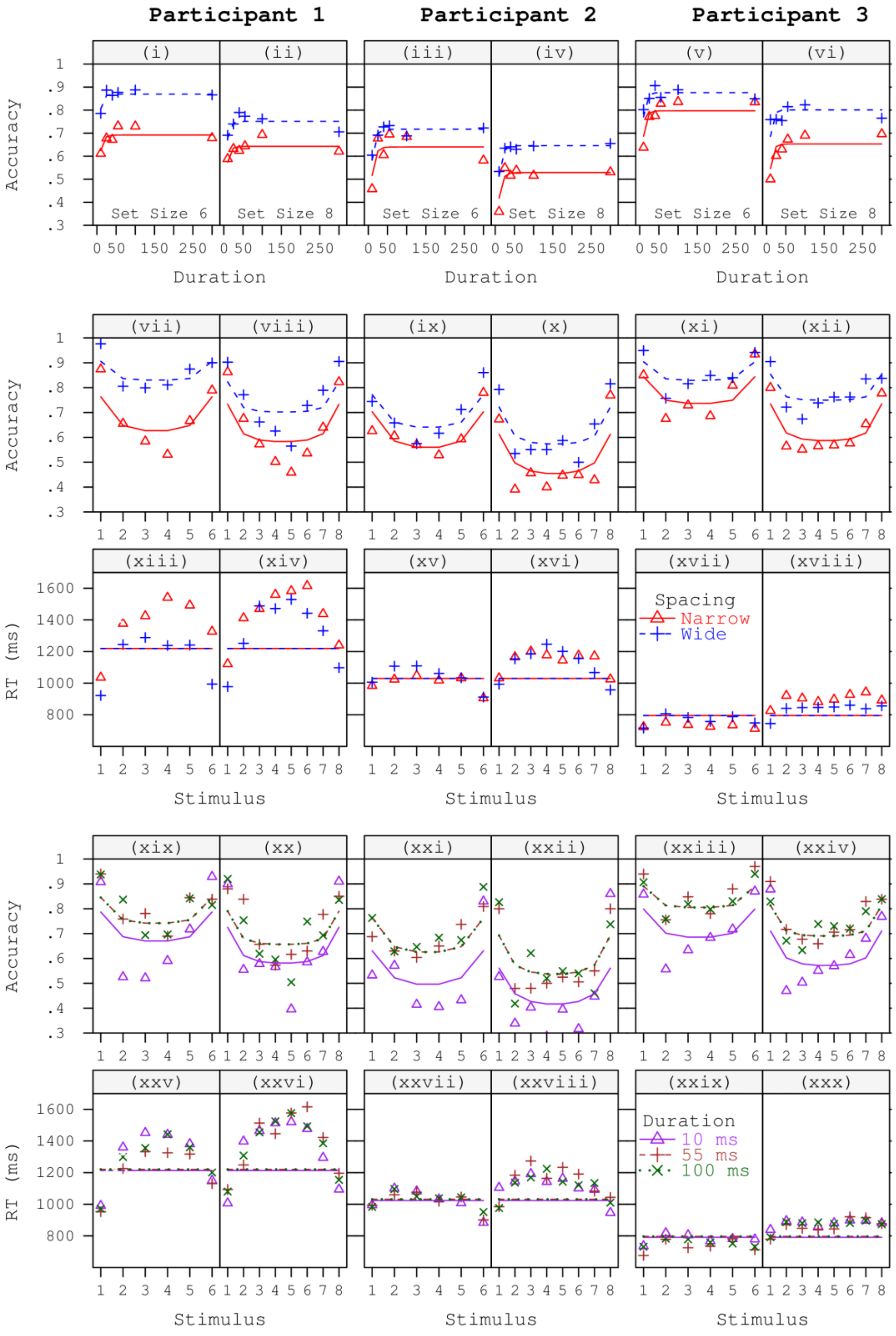

Figure S3. EGCM-RT-*c* predictions. Panels are as per Figure S1.

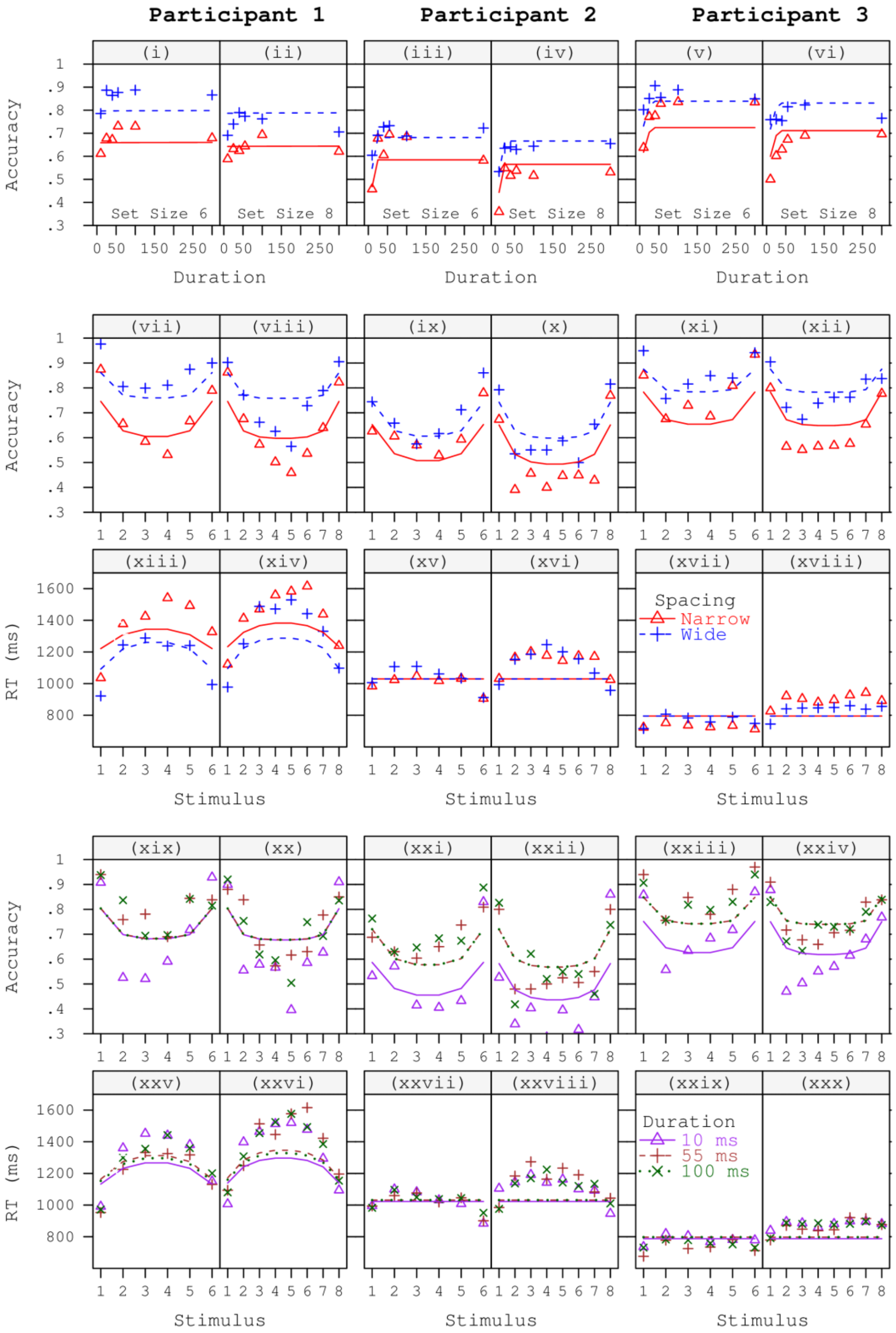

Figure S4. EGCM-RT-T predictions. Panels are as per Figure S1.

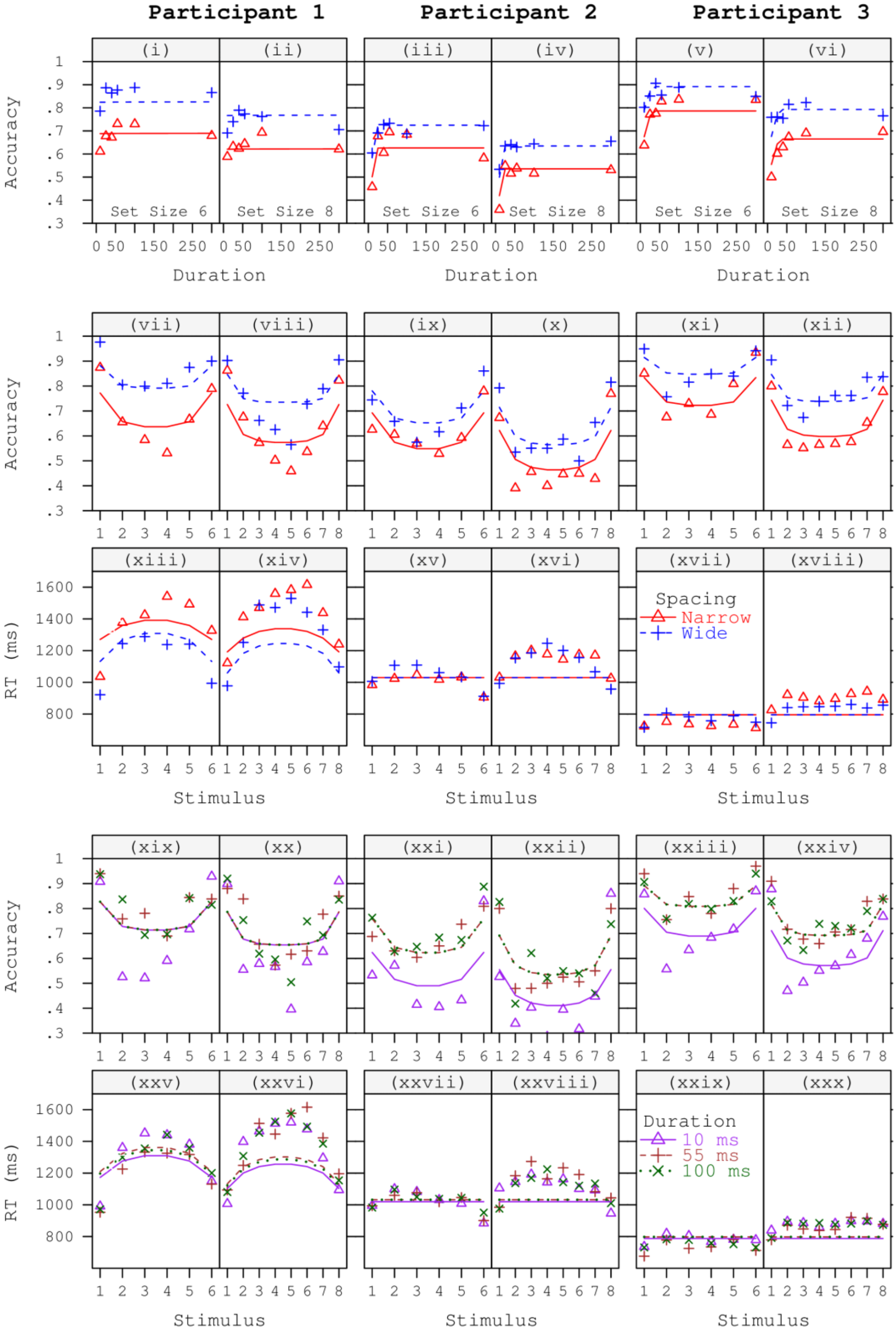

Figure S5. EGCM-RT-T-θ predictions. Panels are as per Figure S1.

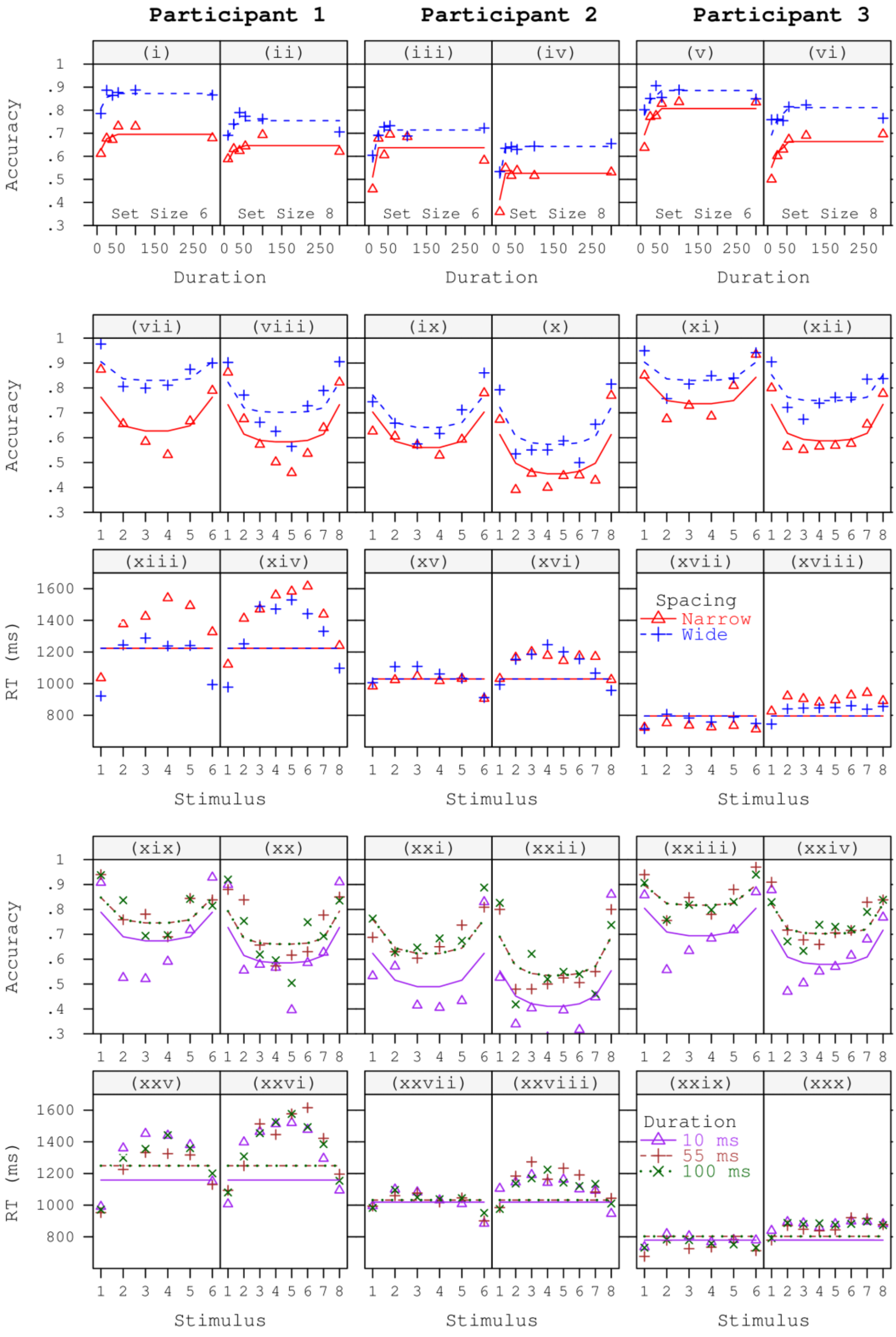

Figure S6. EGCM-RT-T-*c* predictions. Panels are as per Figure S1.

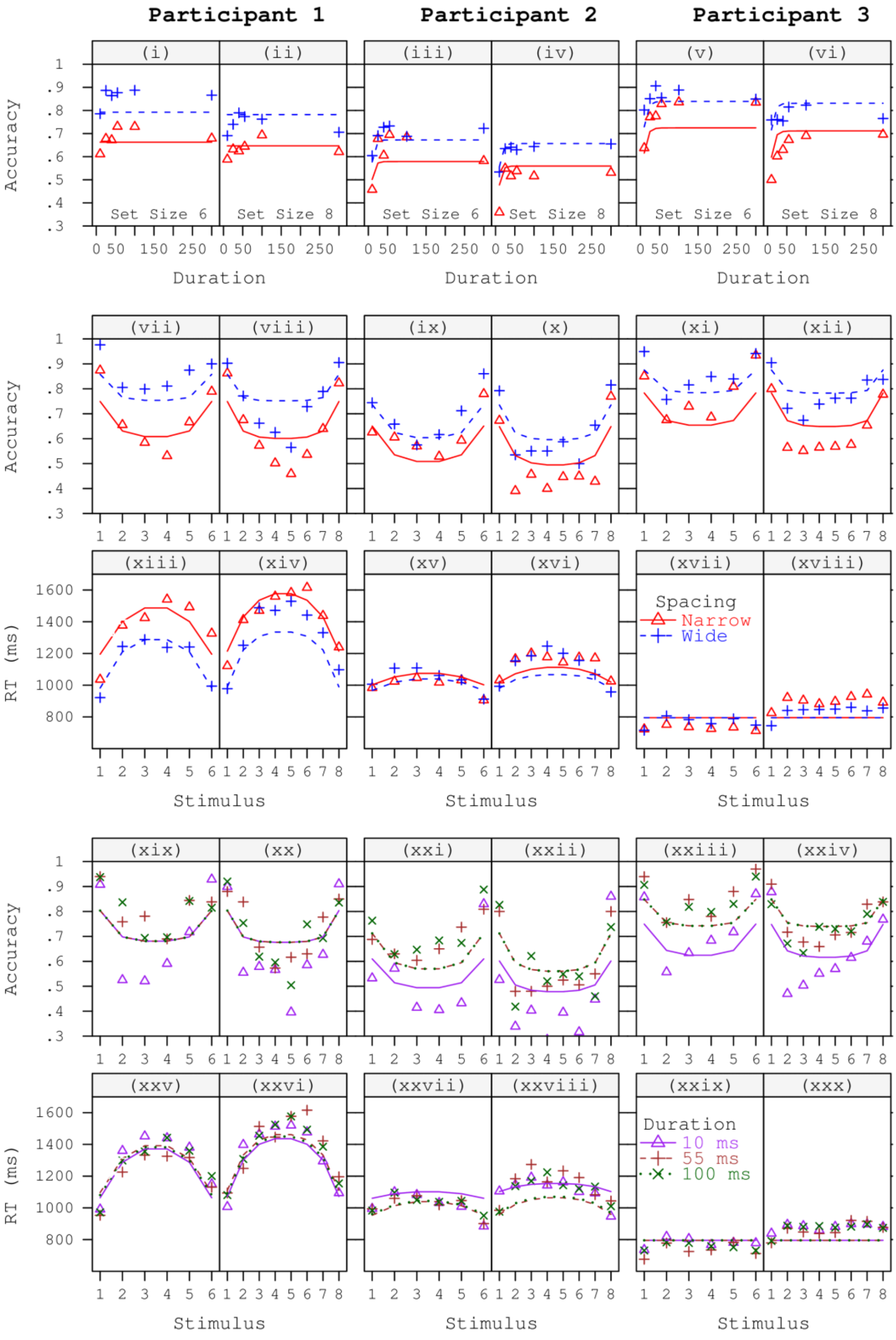

Figure S7. PMEGCM-RT predictions. Panels are as per Figure S1.

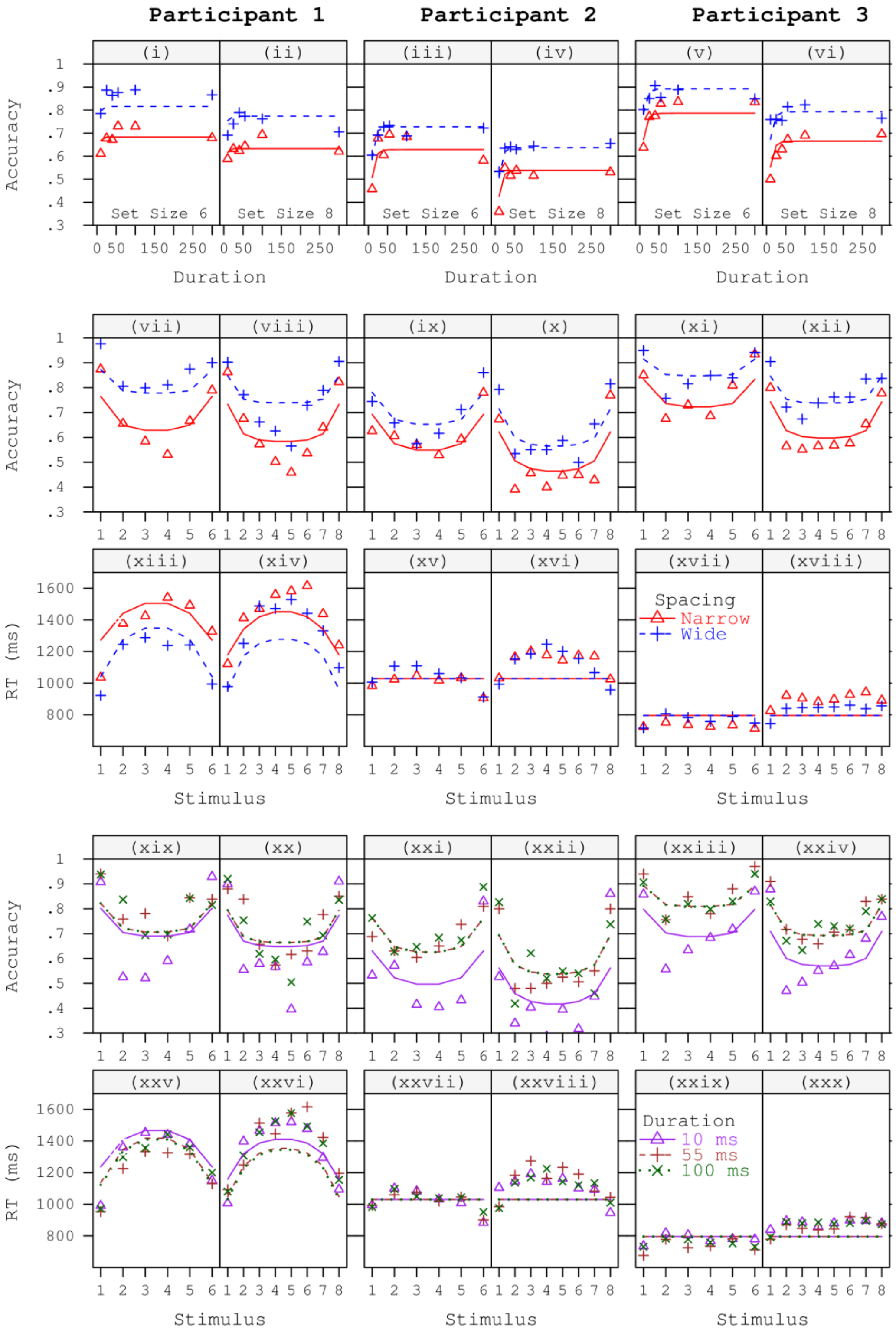

Figure S8. PMEGCM-RT-θ predictions. Panels are as per Figure S1.

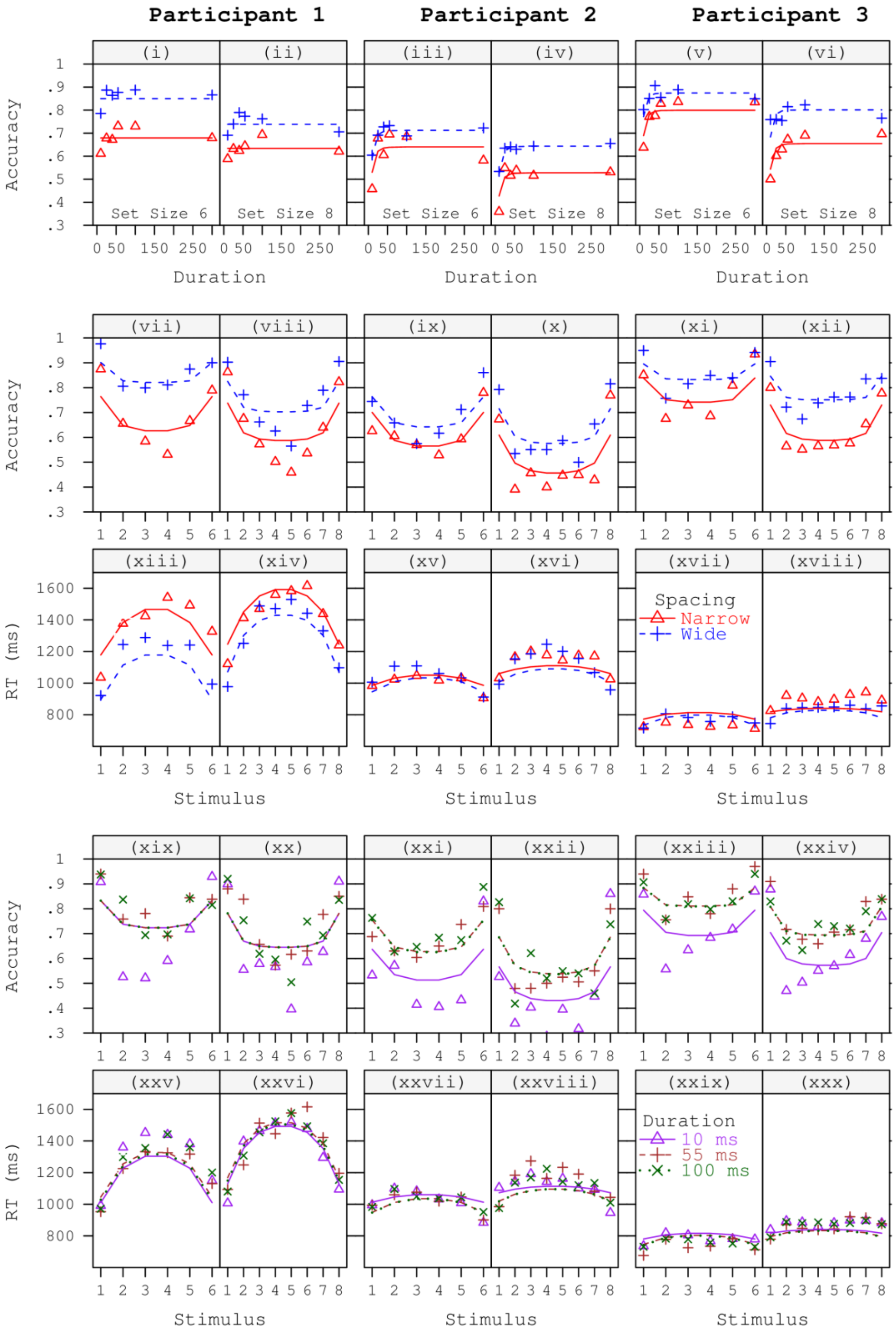

Figure S9. PMEGCM-RT-*c* predictions. Panels are as per Figure S1.

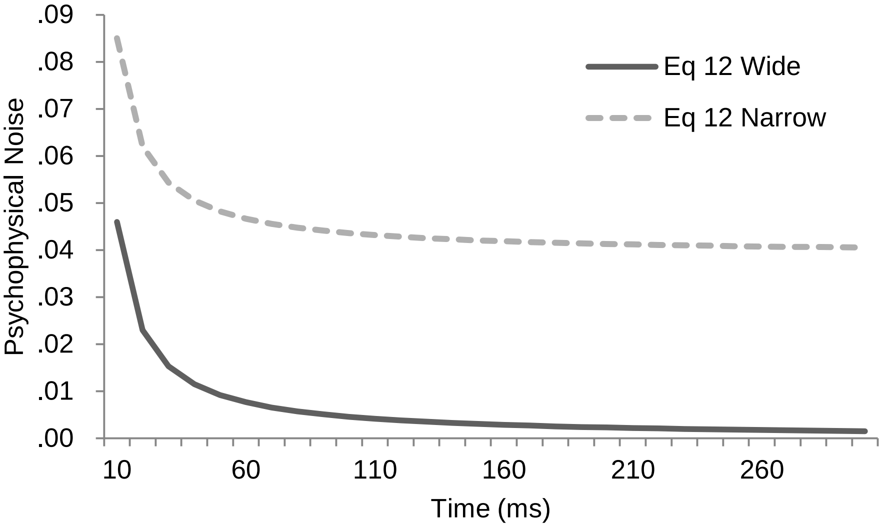

Figure S10. Estimates of perceptual noise from Equation 12 when k_w=0, k_N=.39 and m=.46

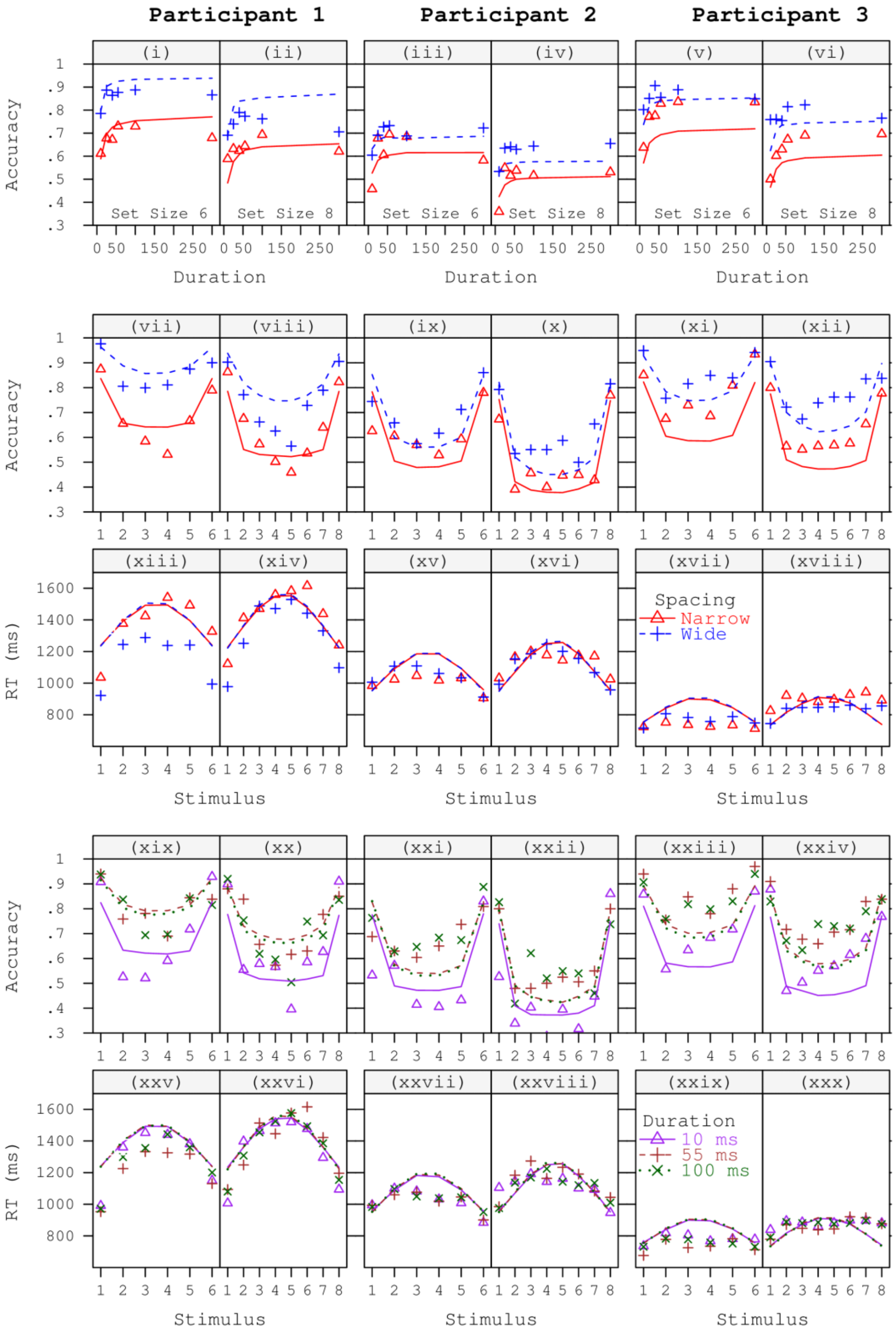

Figure S11. SAMBA predictions. Panels are as per Figure S1.