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Sequential Effects in the Garner Tasks

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Abstract

The distinction between integral and separable dimensions is of central importance to understanding how humans integrate information from multiple stimulus sources. One approach to characterizing stimulus integrality is through a set of speeded categorization tasks most closely associated with the work of Wendell Garner. These tasks demonstrate that integral dimensions result in marked speed up or slow down in responding when there is correlated or irrelevant variation, respectively, compared with a baseline task. Little, Wang & Nosofsky (2016) recently found that the slow down or interference can be largely explained by a reduction in the number of direct repetitions in a modified Garner filtering task. In this paper, we examine a large sample of subjects tested on either separable or integral dimensions to determine the extent of and individual differences in the overall and sequential effects in the *standard* Garner tasks.

Keywords: Categorization; Response Times; Sequential Effects

Introduction

In the study of perceptual decision-making, it is fundamental to understand the distinction between *integrality* and *separability*, as different processing architectures appear to underlie performance with integral and separable dimensions. Information from integral dimensions, which cannot easily be selectively attended to, is best explained as a pooling of information into a single, coactive processing channel (Little et al., 2013). On the other hand, separable dimensions, which can be easily selectively attended to, have been shown to be processed independently in serial or parallel (Fifić et al., 2010). Hence, the notion of integrality and separability must be taken into account in the formal model of categorization and decision making more broadly.

Garner's (1974) Speeded-Categorization Tasks

One classic approach to understanding integrality is Garner's (1974) set of speeded-categorization tasks (see also Algom & Fitousi, 2016, for a review). In these tasks, participants categorize stimuli into two categories as quickly and accurately as possible on each trial. Category membership in these tasks is determined by the stimulus' value on a single relevant dimension. The three major task conditions –*control*, *correlated*, and *filtering* – vary in the structure of the stimulus space, as shown in Figure 1.

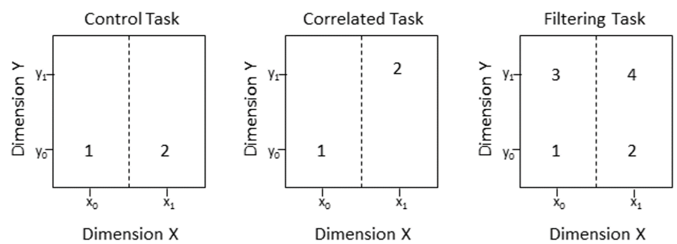

Figure 1. Garner's (1974) control, correlated, and filtering conditions

In the *control* condition, there are two stimuli which only vary along the single relevant dimension (i.e., dimension X in Figure 1). In the correlated condition, there are two stimuli which vary along both the relevant dimension and a second irrelevant dimension. In the filtering condition, there are four stimuli with all possible combinations of relevant and irrelevant dimension values. In all conditions, participants should attend primarily to the relevant dimension while ignoring variation in the irrelevant dimension in order to perform the categorization task accurately and quickly.

For integral dimensions, a robust finding is that subjects have shortest response times (RTs) in the correlated task and the longest RTs in the filtering task. This suggests a correlated-facilitation and filtering- or Garner-interference effect, respectively (Garner, 1974). However, for separable dimensions, RTs across control, correlated, and filtering tasks are relatively invariant (Garner, 1974).

These patterns of RTs arise due to a difference in the ability to selectively attend and process information for integral and separable dimensions (Garner, 1974). When dimensions are separable, participants are easily able to selectively attend to relevant dimension, and as a result, the psychological representation of the stimulus space in all three conditions are collapsed to the single relevant dimension such that the correlated and filtering conditions are isomorphic to the control condition. However, when integral dimensions are used, participants are unable to selectively attend to the relevant dimension, and thus have different psychological representations of the stimulus space for each condition. For instance, as the stimuli vary along both dimensions in the correlated task, when the information from these dimensions are pooled and processed in a single channel, psychological discriminability between stimuli may be increased compared to when the stimuli only vary along one dimension in the control condition. With increased discriminability between stimuli, categorization becomes easier and more efficient resulting in shorter RTs in the correlated task – the correlated-facilitation effect. There are several potential explanations for Garner interference. For one, there are more items in the filtering task than in the control task which may encourage more conservative responding, especially if the stimuli are highly confusable. Alternatively, the increase in the number of items might increase the perceived variability which would act to slow RTs (Nosofsky & Palmeri, 1997).

In a recent paper using a modified version of the Garner task (see Figure 2), Little et al. (2016) showed that one explanation for filtering interference was the reduction of direct sequential repetitions in the filtering condition. That is, with more items, the probability of any one item repeating is reduced compared to the control condition. Repetitions have been show to produce very fast RTs; consequently, the reduction in repetitions results in slower responding (Fletcher & Rabbitt, 1978; Krueger & Shapiro, 1981). Investigations of decomposition (i.e., into sequential effects) of the standard Garner effects (Burns, 2016; Dyson & Quinlan, 2010) have concluded that repetition effects can not be the sole explanation for Garner interference. However, two limitations of these papers are that only a small number of participants was tested (N = 16; Dyson & Quinlan (2010); N = 30; Burns (2016)) and there was no comparison to sequential effects in separable dimension stimuli in either case. Given that the sequential effects in our modified task were highly pronounced (Little et al., 2016), were also present for separable dimensions in the same modified task (Lin & Little, 2017), and that we found considerable individual variability in our modified task, we sought in the present paper to conduct a larger replication of the standard Garner task to examine this decomposition using both integral and separable dimensions.

Sequential Effects

Sequential effects arise due to a reliance on a relative comparison of the current stimulus to the preceding stimulus (or stimuli). These types of effects have been observed in a large variety of categorization tasks (Stewart et al., 2002, see e.g.,) but also in identification (Brown et al., 2007, see e.g.,) and simple choice tasks (Luce, 1986; Jones et al., 2013). One such effect that has been widely studied is the repetition effect, where subjects have higher accuracy and shorter RTs when the current stimulus is identical to the immediately preceding stimulus (Felfoldy, 1974; Lockhead et al., 1978). In their modified task, using integral dimensions, Little et al. (2016) showed that there are complex sequential effects that arise across the control, correlated, and filtering conditions.

1. *Repetition Effect:* Items which were adjacent to category boundary were categorized faster and more accurately when preceded by the same item than when preceded by another item.

2. *Far same category pushing effect:* When the near boundary item was preceded by a far item from the same category, RTs were slower and errors higher than when the near item was preceded by another item.

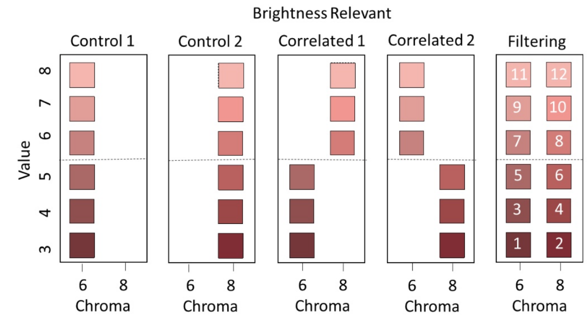

Figure 2. Schematic diagram of the modified Garner-task paradigm using stimuli varying on integral dimensions - brightness and saturation - where the relevant dimension is brightness.

3. *Adjacent opposite category pulling effect:* When the near boundary item was preceded by an adjacent item from the opposite category, RTs were slower and errors higher than when the near item was preceded by another item.

4. *Irrelevant dimension change:* Finally, in the filtering task, the repetition effect was attenuated and the pushing and pulling effects were enhanced when the irrelevant dimension changed (i.e., when there was only repetition of the relevant but not the irrelevant dimension value). This effect emphasizes the role of previous item distance (i.e., from the current item) in determining the magnitude of the sequential effects. This was also evident in the attenuated pushing and pulling effects in the correlated condition (i.e., since the between category items are further apart in that category).

We have recently demonstrated with separable dimensions that the same repetition, pushing, and pulling effects arise even when there was no overall average RT difference between conditions (Lin & Little, 2017). There is no effect of changing the irrelevant dimension in the filtering task with separable dimensions consistent with the notion that attention acts to collapse the separable conditions across the irrelevant dimension.

While there have been some investigations of sequential effects in the standard Garner task (Felfoldy, 1974; Lockhead et al., 1978), there have been few comparisons of sequential effects between integral and separable dimensions. Additionally, there is value in collecting a large replication sample in the standard Garner task, as the magnitude and variability of the standard Garner effects and sequential effect are currently unclear. For instance, not all subjects showed the standard Garner ordering (i.e., correlated RT ¡ control RT ¡ filtering RT) in a modified Garner task. Thus, the present study seeks to quantify the size and variability of the standard Garner effects and several decompositions of those effects (including sequential effects; from Dyson & Quinlan, 2010) using a hierarchical Bayesian analysis.

Method

Two sets of experiments following the general procedure outlined in Garner (1974) were conducted. Experiment 1 used integral dimensions; Experiment 2 used separable dimensions.

Participants In Exp 1, 100 University of Melbourne undergraduates were randomly assigned to either the brightness (N = 50) group or saturation (N=50).[1] One saturation participant was excluded due to an overwritten data file. In Exp 2, 99 students were randomly assigned to either the saturation (N = 49) or line-position (N = 50) group. All received course credit for participation.

Exp 1: Integral Stimuli Stimuli were color squares (100 $\times$ 100 pixels each; Munsell hue 5R) that varied in brightness (*value*) and saturation (*chroma*). The set of four stimuli was created by combining two levels of brightness (values 5, 6) and two levels of saturation (chroma 6, 8). The stimuli were presented on a monitor resolution of 1280 $\times$ 1024.

Exp 2: Separable Stimuli Stimuli were colored rectangles (170 $\times$ 255 pixels) with a black outline and with a small inset black vertical line positioned along the base of the rectangle. The color was selected from the Munsell hue 5R with a brightness value of 5 while the saturation was varied. The line varied by position along the base of the rectangle from the left side of the rectangle. The full set of stimuli was created by combining two levels of saturation (chroma 8, 10) and two line positions (60, 80 pixels from the left). The stimuli were presented on a monitor resolution of 1280 $\times$ 1024.

General Procedure

In both experiments, participants each completed a one-hour categorization task. At the outset, participants were presented with an instruction screen with examples of the stimuli and were told to categorize each stimulus as accurately and quickly as possible. Participants then completed 5 blocks of 24 practice trials followed by 120 experimental trials, and a 6^{th} block of 120 experimental trials.

The control task and correlated tasks were presented over two blocks. In both tasks, only two stimuli of the full set were presented to the participant on each trial. For the subsequent block of the control task, the irrelevant dimension value was switched. For the subsequent block of the correlated task, the relevant and irrelevant dimension values of the two stimuli were both switched.

The filtering task was presented over two consecutive blocks without practice trials for the second block. The blocks of tasks were counterbalanced and the order of presentation of individual stimuli on each trial was randomized anew within each block.

On each trial, a fixation cross was presented for 1500ms, followed by the stimulus. The participant then decided whether the stimulus belonged to category A or B. Response choice and response time (RT) were recorded via button press of a customized RT box Li et al. (2010). The stimulus remained on screen until a button press was made or until the 5000ms response deadline. Full feedback (i.e., "right", "wrong") was provided for the 24 practice trials; only incorrect response feedback was provided for experimental trials. If a response was not made before the response deadline, feedback "too slow" was given. The feedback remained on screen for 2000ms.

[1] A programming error meant that all participants in Experiment 1 completed the brightness-relevant task.

Data Analysis

We applied two hierarchical Bayesian models. For the first model, we found the posteriors for a single group distribution for each of the items in the control, correlated, and filtering task in each of the integral and separable experiments. For the second model, we found the posteriors for distributions of each sequential order for each condition across both experiments. That is, we estimated the posterior for when the relevant dimension value repeated and the irrelevant dimension value repeated (hereafter, RR), for when the relevant dimension changed but the irrelevant dimension repeated (CR), when the relevant dimension repeated but the irrelevant dimension change (RC), and for when both the relevant and irrelevant dimensions changed (CC). The control task only contains the RR and CR conditions, the correlated task contains the RR and CC conditions, and the filtering task contains all four conditions.

For each experiment i, each subject j, and each task (or sequence condition) k, we estimated the rt as a lognormal distribution, $rt_{ijk} \sim LogN(\mu_{ik}, \sigma_{ik})$. The prior over the subject means was a normal distribution, $\mu_{ik} \sim N(M_k, S_k)$, and the prior over the subject precision ($1/\sigma_{ik}$) was a gamma distribution, $1/\sigma_{ik} \sim Gamma(a_k, b_k)$. Hyperpriors were relatively non-informative, $M_k\ U(0,7)$, $S_k \sim U(0,500)$, $a_k \sim U(.5,100)$, and $b_k \sim U(.5,100)$, where $U(x,y)$ is a uniform distribution over the range $[x,y]$. The models were implemented in JAGS (Plummer, 2003) for which we collected 1000 samples after 1000 burn-in samples from two MCMC chains. Plots of these chains indicated good convergence.

Results

The estimated rt means and variances are on a logarithmic scale and not the scale of the original RT data. Hence, to summarize the effects, we converted the posterior group log-Normal distribution means, M, and standard deviation, to the RT scale using the following transformation:

$$\tilde{M}_k = exp(M_k + \frac{S_k^2}{2})$$

$$\tilde{S}_k = \sqrt{exp(2M_k + S_k^2)exp(S_k^2 - 1)}$$

Overall Condition Analysis

We first analysed the overall difference between condition by taking the difference between the Control and Correlated posterior estimates (left panel, Figure 3) and between the Control

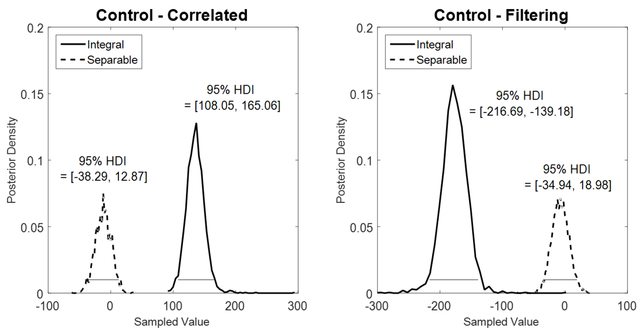

Figure 3. Posterior distributions for the difference between control and correlated overall mean RTs (left panel), and the difference between between control and filtering overall mean RTs (right panel). The solid line shows the distribution for the integral posterior and the dotted line shows the posterior for the separable condition.

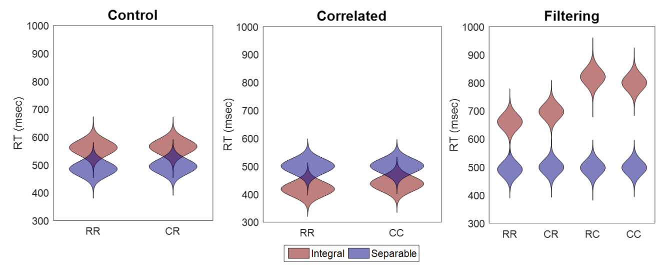

Figure 4. Posterior distributions for the transformed logNormal groups means for the Control condition (RR & CR; Left panel), Correlated condition (RR & CC; Middle panel), and Filtering condition (CC, CR, RC, CC; Right panel)

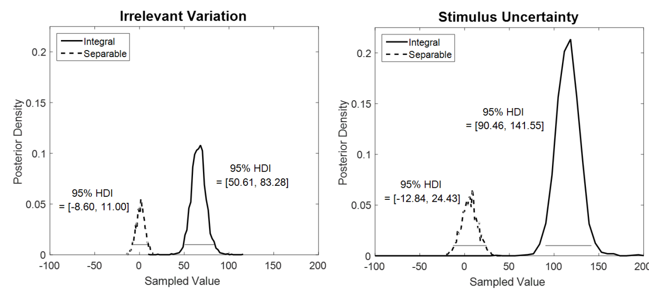

Figure 5. Posteriors distributions for irrelevant feature variation (left panel) and stimulus uncertainty (right panel) components of filtering interference for both integral and separable dimensions.

task and the filtering task (right panel, Figure 3). We note that there were no strong qualitative individual differences; only quantitative variation.

For the comparisons to the correlated condition, positive values would indicate shorter RTs in the correlated condition than the control condition. Analogously, for the comparison to the filtering condition, negative values indicate longer RTs in the filtering condition than in the control condition. As shown in Figure 3, the posterior distributions for the separable conditions have substantial density over 0 indicating no overall effect of condition. For the integral conditions, the distributions had the most density over positive and negative difference values for the correlated and filtering comparisons, respectively. Hence, we've replicated the standard Garner result and have shown that all subjects in our experiment show this pattern of results.

Sequential Item Analysis

Figure 4 shows the posterior distributions for each of the item conditions. For the separable dimensions condition, posterior distributions for item conditions appear to be relatively invariant across the control, correlated, and filtering tasks, indicating little or no sequential effects. The posterior distributions for the integral dimension condition reveals a more complex pattern of item condition effects. In the control task, the posterior distributions for RR and CC indicate no sequential effects. In the correlated task, the posterior distribution for RR lies slightly lower than CC, suggesting a repetition effect. In the filtering condition, posterior RTs are markedly slower for irrelevant dimension changes (i.e., RC and CC), and quickest when the stimulus is repeated (i.e., RR).

We summarized these distribution by computing several effect decompositions derived by Dyson & Quinlan (2010).

Filtering interference Note that overall filtering interference can be decomposed into sequential components as: $[RR_{filt} + RC_{filt} + CR_{filt} + CC_{filt}]/4 - [RR_{cont} + CR_{cont}]/2$, which "filt" refers to the filtering condition and "cont" to the control condition. This overall measure can be further decomposed into the following two components:

1. A measure of irrelevant feature variation, which is positive if there is a cost when the irrelevant dimension changes: $[RR_{filt} + RC_{filt} + CR_{filt} + CC_{filt}]/4 - [RR_{filt} + CR_{filt}]/2$
2. A measure of stimulus uncertainty, which is positive if there is a cost associated with having more stimuli in the filtering condition controlling for changes in the irrelevant dimension: $[RR_{filt} + CR_{filt}]/2 - [RR_{cont} + CR_{cont}]/2$

These two effects are shown in Figure 5. For these figures, negative values indicate RT benefits (i.e., shorter RT) while positive values indicate RT costs (i.e., longer RT) for the respective effect. The posterior distribution for both effects for separable dimensions have substantial density over zero, indicating no irrelevant feature variation or stimulus uncertainty effects. In contrast, the posterior distributions for integral dimensions have substantial density over positive values, indicating RT costs as a result of irrelevant variation and stimulus uncertainty. Furthermore, stimulus uncertainty appears to contribute to filtering interference more than irrelevant variation for the integral dimensions condition.

Correlated benefit In the correlated condition we conducted a corresponding decomposition (again following

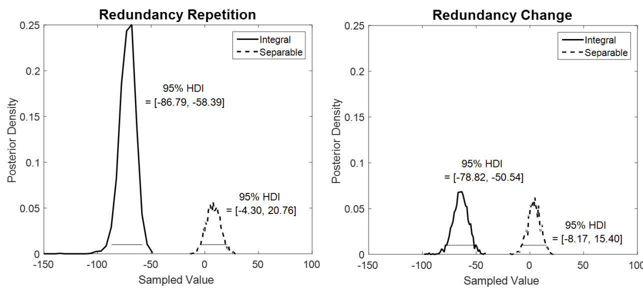

Figure 6. Posterior distributions for redundancy repetition (left panel) and redundancy change (right panel) components of correlated facilitation for both integral and separable dimensions.

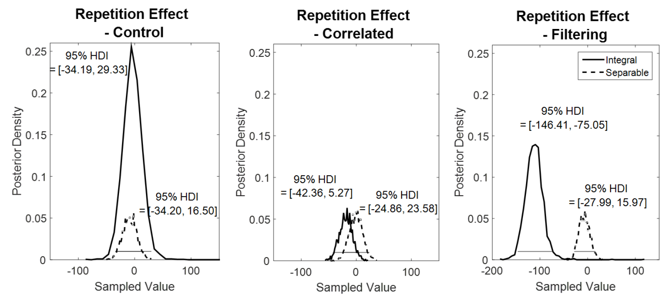

Figure 7. Posterior distributions for the repetition effect in control, correlated, and filtering tasks for both integral and separable dimensions.

Dyson & Quinlan 2010) as: $[RR_{corr} + CR_{corr}]/2 - [RR_{cont} + CR_{cont}]/2$.

This overall measure can be further decomposed into:

1. The effect of redundancy repetition, which indexes the effect of changing both dimensions: $[RR_{corr} - RR_{cont}]/2$
2. The effect of redundancy change, which indexes the effect of additional irrelevant dimension variation in the correlated condition compared to the control condition: $[CC_{corr} - CR_{cont}]/2$.

These effects are shown in Figure 6. For separable dimensions, the posterior distributions for both redundancy repetition and redundancy change have substantial density over zero, indicating no overall correlated facilitation effect. For integral dimensions, both redundancy repetition and redundancy change have substantial value over negative values, indicating RT benefits. In addition, the components appear to contribute approximately equally to the overall correlated facilitation effect.

Repetition Effect Finally, for all three conditions we computed the effect repeating an item compared to switching an item (i.e., in the control and correlated conditions; in the filtering condition, we compared repetition to the average of the other three item RTs). [2] This repetition measure is computed as:

$$\begin{aligned} Control\ Repetition &= RR_{cont} - CR_{cont} \\ Correlated\ Repetition &= RR_{corr} - CC_{corr} \\ Filtering\ Repetition &= RR_{filt} - [CR_{filt} + RC_{filt} + CC_{filt}]/3 \end{aligned}$$

This measure can also be interpreted to indicate a repetition effect (i.e., shorter RTs as a result of repetition in both dimensions). A negative value indicates a repetition effect

In the control condition, the distributions for both integral and separable dimensions are centered around zero, suggesting no repetition effect. In the correlated condition, the posterior distributions for both integral and separable dimensions have a substantial density over negative values, indicating a slight repetition effect. The repetition effect for integral dimensions also appears to be marginally stronger than for separable dimensions; though even here, both distributions have 95% highest posterior density intervals which overlap 0. In the filtering condition, the distribution for separable dimensions has substantial density over zero, indicating no repetition effect. However, the distribution for integral dimensions lies mainly over negative values, indicating the presence of a strong repetition effect.

Discussion

Overall, the hierarchical Bayesian approach in the present study revealed reliably strong standard Garner effects, showing correlated facilitation and filtering interference with integral dimensions but not with separable dimensions. A further decomposition of the Garner effects into sequential item conditions, following Dyson & Quinlan (2010), provide further insight into the underlying mechanisms of perceptual decision-making. Notably, we found little evidence for any individual differences.

One notable finding is that no sequential effects were found with separable dimensions in the standard Garner task. This result is in contrast to the sequential effects found with separable dimensions in the modified Garner task (Lin & Little, 2017). One potential explanation could be that the presence and magnitude of sequential effects depends on task complexity. For example, Bentin & McCarthy (1994) found that immediate repetition provides a relatively larger advantage in lexical decision and face recognition tasks compared to simpler discrimination tasks, as it eliminated the need for more complex processes such as accessing semantic memory. Similarly, as the standard Garner task has a much smaller stimulus space compared to the modified Garner task, repetitions may provide a large benefit for the modified task but a much smaller or no RT benefit, and as a result, no sequential effects arise in the standard task. On the other hand, we have only examined the effects of a single preceding item; in simple RT tasks (i.e., with two stimuli), there are complex sequential ef-

[2] For the correlated condition, this provides an index of the *bypass strategy* (Dyson & Quinlan, 2010). The bypass strategy describes a strategy whereby participants monitor only the trial-by-trial sequences making the same response as on the previous trial when the stimulus is the same as the previous trial and switching responses when the stimulus changes.

fects extending up to five items back reflecting the influence of repetitions and alternations (Jones et al., 2013).

Another important result is that stimulus uncertainty contributes to filtering-interference more than irrelevant feature variation. An explanation could be that the lack of interference from irrelevant feature variation can be attributed to the integrality of dimensions. If dimensions are less integral and easier to selectively attend to, then the irrelevant variation would not contribute to interference, for example, in the separable dimensions case. It should also be noted that it is difficult to isolate stimulus uncertainty and irrelevant feature variation in the standard Garner task, as an increase in the number of irrelevant dimensions is associated with a larger number of stimuli. Even though these measures attempt to isolate trials where only stimulus uncertainty or irrelevant variation changes, it is unclear whether the larger context of the task has no impact. Burns (2016) attempted to disentangle these two components by introducing a 3-dimensional Garner task where irrelevant variation could be increased without affecting stimulus uncertainty, and demonstrated that irrelevant variation alone can increase interference substantially. In order to further evaluate the components underlying filtering-interference, promising avenues for future work might be to measure these decomposition effects with a variety of different dimensions varying on integrality or to carefully manipulate stimulus uncertainty and irrelevant variation within Burns's (2016) 3-dimensional Garner task.

Acknowledgments

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